International Journal of Greenhouse Gas Control

Utilisation of Artificial Intelligence based Time-Series Prediction to validate Carbon Containment in Injection Well in Illinois Basin

--Manuscript Draft--

Manuscript Number:	JGGC-D-23-00588R1
Article Type:	Full Length Article
Keywords:	low-carbon, time-series, neural network, LSTM, carbon capture, injection pressure, monitoring, plume migration
Corresponding Author:	Munish Kumar Singapore University of Social Sciences SINGAPORE
First Author:	Munish Kumar
Order of Authors:	Munish Kumar
	Kannappan Swaminathan
Abstract:	Carbon Capture Utilisation and Storage (CCUS) involves capturing CO2 emissions and securely storing them in geological formations. CCUS is gaining significance in global efforts to meet ambitious climate goals. The storage of CO2 typically occurs through injection into saline aquifers, depleted oil and gas fields, or for Enhanced Oil Recovery (EOR). However, all methods require a deep understanding of subsurface geology and the ability to monitor CO2 behaviour during injection and storage. Pilot projects like the Illinois Basin - Decatur Project demonstrated the practical feasibility of storing CO2 underground. The injection spanned three years, during which nearly 999,215 tonnes of CO2 was stored. Monitoring was carried out through a pair of wells equipped with sensors to track pressure and temperature at various depths. This paper focuses on using time series injection data and monitoring information to predict changes in injection rates for the carbon capture well. We perform the prediction using Long Short-Term Memory (LSTM) neural networks (NN). These changes, represented as deltas (Δ) in injection rates between time t and time (t-1), are crucial indicators of carbon containment and migration within the well. By correlating these rate changes with other well parameters, this approach serves as a checkpoint against unwanted carbon migration or losses during the injection process. Machine learning methods are applied to forecast these injection rate deltas based on monitoring data, thereby validating the effectiveness of carbon containment during injection.
Suggested Reviewers:	Alessandro Romagnoli A.Romagnoli@ntu.edu.sg
	PETER FANTKE PEFAN@DTU.DK
	Kamaljit Singh K.Singh@hw.ac.uk
	Praveen Linga chepl@nus.edu.sg
	Ning YAN ning.yan@nus.edu.sg
	Karen Lythgoe karen.lythgoe@ed.ac.uk
Response to Reviewers:	

Cover letter to the Editor

Manuscript title: Utilisation of Artificial Intelligence based Time-Series Prediction to validate Carbon Containment in Injection Well in Illinois Basin

Name of the Corresponding Author: Munish Kumar
Name(s) of all other authors: Kannappan Swaminathan
Type of Manuscript: Research Article

This manuscript is appropriate for *the International Journal of Greenhouse Gas Control (IJGGC)* as to this authors knowledge, there is a limited pool of information combining engineering, data science and artificial intelligence for time series prediction and forecasting of fields undergoing carbon capture and storage. We primarily think this is due to the lack of publicly available data on how CO_2 wells behave once injection begins. We are both practicing energy professionals and hope that our work can be utilized by other like-minded scientists as they attempt to predict injection well behavior and better identify anomalies to ensure CO_2 containment in the long run.

We have realized, through this work, that having a holistic understanding of both practical petroleum engineering and data science within the carbon capture and storage realm can either help to derisk opportunities, or at the very minimum, explain why a project may perform in a sub-optimal manner. This makes our work important and the journal the appropriate avenue to publish it.

The manuscript has been checked by a native English speaker with expertise in the field of energy. In this authors opinion, this work would appeal to both a popular audience and scientific audience.

The manuscript, or its contents in some other form, has not been published previously by the author and is not under consideration for publication in another journal at the time of submission. The manuscript does not have any supporting information and/or Review-Only Material.

Yours sincerely,

Dr Munish Kumar
October 03, 2023

Response to Editor:

Thank you for arranging for the article review. We have made the revisions requested to the manuscript and addressed the comments from the reviewers individually within separate documemts.

We would additionally like to share some feedback regarding the reviewers. Having incorporated the comments of the reviewers as best as we can, we would like to point out that:

- Reviewer #1 has accepted our paper with minor revisions. We note that he/she did not have major comments and was generally complementary. We have made the necessary changes requested.

- Reviewer #2 main point was for us to enhance the paper via deeper technical discussions and application, which we can appreciate. We (the authors) are both engineers by background and are fully supportive of "applied research" (which we hope this is) rather than more theoretical or abstract machine learning models. We have tried to incorporate this feedback through the inclusion of an additional paragraph where we discuss the business merits of this method.

- Reviewer #3 has asked for us to review the data from a more geological perspective. We appreciate this view, and have done our best to incorporate more of this in our paper. However, we want to point out that the reviewer must understand that our aim is machine learning and prediction, and not necessarily a detailed deep dive into the geology or reservoir properties of the data set. The reviewer has stated that there is no need for complicated methods to analyse CO_2 containment; the reviewer appears to be alone in this view as the other 3 reviewers have no such issue with the paper.

- Reviewer #4 appeared to be intrigued by our work and generally supportive, asking us to put in some arguments around the challenges of predicting CO_2 injection. We have incorporated this and think it will satisfy his/her requirements.

We hope this adequately addresses the concerns raised by the reviewers and look forward to hearing back from you.

Thank you

Dr Munish Kumar and Kannappan Swaminathan

Response to Reviewer #1:

Thank you for your feedback. We have made the revisions requested to the manuscript and addressed your comments in this document in blue. We hope this adequately addresses the concerns raised.

1. This work is a good demonstration of how machine learning and artificial intelligent can be used to effectively monitor carbon plume migration either from injection or monitoring wells by correlating change in injection rate to the behavior of other dynamic parameters. Although, the approach has been applied in many fields such reservoir parameters prediction, flow rate prediction, etc., the use of LSTM for data forecasting is adequately justified. It is the first application to injection rate monitoring in CCUS, although there is more room for model optimization and improvement. Overall, it is a well written manuscript and I recommend that it should be accepted with minor revision following some corrections.

Author Response: Thank you very much

2. Some of the information I the abstract can be moved to the introduction.

   Line 12-18 should be moved to introduction.

Author Response: Noted; it is already mentioned in the introduction from lines 49-58 in the original manuscript. We have now removed it from the abstract entirely.

Line 60 – "Given the early stage of this technique, it is imperative to initiate pilot development and validate the technology" should be reworded.

CCUS technology is about 40-year-old not in pilot stage, there are many demonstrations of capabilities around the world especially in oil and gas industries.

Author Response: Noted, we have removed the statement.

Line 159-162-Please clarify or explain why 67% of data was use for training the model and 33% for validation. Why did use this percentage? Would 50:50 change the accuracy of the model?

Author Response: The 2/3: 1/3 training: validation ratio is a generalised "rule of thumb" and is just dependent on the programmers view at the time of code writing. In our experience, models can also be built with a 70:30 or 80:20 ratio.

We opted in this case to set aside more data as a validation set because we wanted to build a model that we hoped would be more insensitive to noise. In other words, the less data we use in our training set, the more generalised the model, but use too little and we ran the risk of underfitting, therefore limiting its usefulness as a predictor.

Similarly, if we used too much data for training, we would have created an overfitted model that would not be sufficiently generalised. This ratio was thus a good comprise in this authors opinion.

Line 328-32- Clarify the difference between figure 6a and 6b (Anomalies versus variation plot; notice that one is in months while the other appear to be in days in 2012)? In figure 6b, the injection difference does not match the LSTM prediction very well. Can you explain why? Why are this data set chosen for the validation?

Author Response: The reviewer is correct in that 6(a) is in months and demonstrates that general variabilities can be captured by the model, as per design. 6(b), which is in days, then shows that as much as possible, small-scale perturbations are somewhat predicted, albeit not perfectly, because at such small scales, the data starts to behave like "noise", with low amplitude, high frequency characteristics that any model would be hard pressed to predict 100%. At this scale it is most important to capture the statistical behaviour than point-for-point data.

To the editor, here are our responses/explanations based on the email:

International Journal of Greenhouse Gas Control

Reviewer's Responses to Questions

Note: In order to effectively convey your recommendations for improvement to the author(s), and help editors make well-informed and efficient decisions, we ask you to answer the following specific questions about the manuscript and provide additional suggestions where appropriate.

1. Are the objectives and the rationale of the study clearly stated?

Please provide suggestions to the author(s) on how to improve the clarity of the objectives and rationale of the study. Please number each suggestion so that author(s) can more easily respond.

Reviewer #1: This work is a good demonstration of how machine learning and artificial intelligent can be used to effectively monitor carbon plume migration either from injection or monitoring wells by

Author Response: Thank you

---

2. If applicable, is the application/theory/method/study reported in sufficient detail to allow for its replicability and/or reproducibility?

Please provide suggestions to the author(s) on how to improve the replicability/reproducibility of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #1: Mark as appropriate with an X:
Yes [] No [x] N/A []
Provide further comments here:

Author Response: Thank you

---

3. If applicable, are statistical analyses, controls, sampling mechanism, and statistical reporting (e.g., P-values, CIs, effect sizes) appropriate and well described?

Please clearly indicate if the manuscript requires additional peer review by a statistician. Kindly provide suggestions to the author(s) on how to improve the statistical analyses, controls, sampling mechanism, or statistical reporting. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #1: Mark as appropriate with an X:
Yes [x] No [] N/A []
Provide further comments here: The manuscript is in the domain of artificial intelligent. Perhap, mathematical modelling expert can provide more useful insight for the work. I recommend Prof. Hassan Hassanzadeh (University of Calgary), for further review of models.

Author Response: Thank you

---

4. Could the manuscript benefit from additional tables or figures, or from improving or removing (some of the) existing ones?

Please provide specific suggestions for improvements, removals, or additions of figures or tables. Please number each suggestion so that author(s) can more easily respond.

Reviewer #1: no

Author Response: Thank you

---

5. If applicable, are the interpretation of results and study conclusions supported by the data?

Please provide suggestions (if needed) to the author(s) on how to improve, tone down, or expand the study interpretations/conclusions. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #1: Mark as appropriate with an X:
Yes [x] No [] N/A []
Provide further comments here: The results from the models are well interpreted and are well supported in the conclusion.

Author Response: Thank you

---

6. Have the authors clearly emphasized the strengths of their study/theory/methods/argument?

Please provide suggestions to the author(s) on how to better emphasize the strengths of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #1: The study applies artificial intelligence to determine the effectiveness of CO2 containment. it is a new application of method to CCS. The LSTM model can be expatiated more to help reader follow the application.

Author Response: Thank you

---

7. Have the authors clearly stated the limitations of their study/theory/methods/argument?

Please list the limitations that the author(s) need to add or emphasize. Please number each limitation so that author(s) can more easily respond.

Reviewer #1: Yes they did mentioned that the model can be improved by improving the feedback loop for better prediction accuracy.

Author Response: Thank you

---

8. Does the manuscript structure, flow or writing need improving (e.g., the addition of subheadings, shortening of text, reorganization of sections, or moving details from one section to another)?

Please provide suggestions to the author(s) on how to improve the manuscript structure and flow. Please number each suggestion so that author(s) can more easily respond.

Reviewer #1: It is easy to follow

Author Response: Thank you

---

9. Could the manuscript benefit from language editing?

Reviewer #1: No

Author Response: Thank you

Response to Reviewer #2:

Thank you for your feedback. We have made the revisions requested to the manuscript and addressed your comments in this document in blue. We hope this adequately addresses the concerns raised.

To the editor, here are our responses/explanations based on the email:

International Journal of Greenhouse Gas Control
Reviewer's Responses to Questions

Note: In order to effectively convey your recommendations for improvement to the author(s), and help editors make well-informed and efficient decisions, we ask you to answer the following specific questions about the manuscript and provide additional suggestions where appropriate.

1. Are the objectives and the rationale of the study clearly stated?

Please provide suggestions to the author(s) on how to improve the clarity of the objectives and rationale of the study. Please number each suggestion so that author(s) can more easily respond.

Reviewer #2: Although the authors have attempted to analyze some prediction methods, a deeper discussion would be expected. Otherwise, the motivation for this study may not be sufficiently strong.

Author Response: Thank you. We have included an additional section explaining the motivation in the introduction.

---

2. If applicable, is the application/theory/method/study reported in sufficient detail to allow for its replicability and/or reproducibility?

Please provide suggestions to the author(s) on how to improve the replicability/reproducibility of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #2: Mark as appropriate with an X:
Yes [X] No [] N/A []
Provide further comments here:
While basic metrics like mean square error and MAE are used to evaluate your regression model, such validation may not be strong enough. Therefore, it is suggested to design and incorporate other cross-validation techniques or specific metrics for a more robust evaluation.

Author Response: We thank the reviewer for this response, but the reviewer is mistaken. We did do a k-fold cross-validation methods for this work (line 255-256).

---

3. If applicable, are statistical analyses, controls, sampling mechanism, and statistical reporting (e.g., P-values, CIs, effect sizes) appropriate and well described?

Please clearly indicate if the manuscript requires additional peer review by a statistician. Kindly provide suggestions to the author(s) on how to improve the statistical analyses, controls, sampling mechanism, or statistical reporting. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #2: Mark as appropriate with an X:
Yes [] No [X] N/A []
Provide further comments here:
A more profound discussion should be provided to support the algorithm and its engineering applications.

Author Response: Thank you. We have included a real-world case study in the introduction section.

---

4. Could the manuscript benefit from additional tables or figures, or from improving or removing (some of the) existing ones?

Please provide specific suggestions for improvements, removals, or additions of figures or tables. Please number each suggestion so that author(s) can more easily respond.

Reviewer #2: The figure quality needs improvement; some numbers are unclear, such as in Figure 2. Please ensure consistency in formatting figures/tables within the context, such as the font in Figure 3.

Figure 4 requires correction; some information inside has overlapped, which does not meet publishing standards. Additionally, please check and rectify similar problems in all other figures.

Author Response: Noted; we have edited where possible.

---

5. If applicable, are the interpretation of results and study conclusions supported by the data?

Please provide suggestions (if needed) to the author(s) on how to improve, tone down, or expand the study interpretations/conclusions. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #2: Mark as appropriate with an X:
Yes [] No [] N/A [X]
Provide further comments here:
A more profound discussion should be provided to support the algorithm.

Author Response: Thank you. We have included this discussion in the introduction section.

---

6. Have the authors clearly emphasized the strengths of their study/theory/methods/argument?

Please provide suggestions to the author(s) on how to better emphasize the strengths of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #2: No. The introduction part begins with human activities, which is too broad. It is suggested to concentrate on CCUS from the outset.

Author Response: Thank you. We have removed the first paragraph of the introduction.

---

7. Have the authors clearly stated the limitations of their study/theory/methods/argument?

Please list the limitations that the author(s) need to add or emphasize. Please number each limitation so that author(s) can more easily respond.

Reviewer #2: Deeper discussion is necessary rather than applying a machine learning method to CCUS.

Author Response: Thank you. We have highlighted its uses in the introduction.

---

8. Does the manuscript structure, flow or writing need improving (e.g., the addition of subheadings, shortening of text, reorganization of sections, or moving details from one section to another)?

Please provide suggestions to the author(s) on how to improve the manuscript structure and flow. Please number each suggestion so that author(s) can more easily respond.

Reviewer #2: The literature review has been separated from the introduction. However, these two parts lack correlation, and it is recommended to transition between them more smoothly.

Author Response: We thank the reviewer and have tried to synergize the section better.

---

9. Could the manuscript benefit from language editing?

Reviewer #2: Yes

Author Response: We thank the reviewer; however, we do not know what changes the reviewer is recommending. This reviewer is also alone in this recommendation, as the remining 3 reviewers have not singled this out.

<u>Response to Reviewer #3:</u>

Thank you for your feedback. We have made the revisions requested to the manuscript and addressed your comments in this document in blue. We hope this adequately addresses the concerns raised.

To the editor, here are our responses/explanations based on the email:

<u>International Journal of Greenhouse Gas Control</u>
Reviewer's Responses to Questions

Note: In order to effectively convey your recommendations for improvement to the author(s), and help editors make well-informed and efficient decisions, we ask you to answer the following specific questions about the manuscript and provide additional suggestions where appropriate.

1. Are the objectives and the rationale of the study clearly stated?

Please provide suggestions to the author(s) on how to improve the clarity of the objectives and rationale of the study. Please number each suggestion so that author(s) can more easily respond.

Reviewer #3:

a. main points in conclusion: As stated in line 412 & 413 of the Conclusion, the model was made to predict the injection rate changes of the CO2 injection by using some of the 34 contemporarily recorded other monitored parameters. And lines 418 & 419 state that the model's primary objective is to detect anomalies and alert operators to closely inspect the well for potential leaks.
Authors response: Thank you for the comment; there is nothing to action here.

b. There is nothing in the report to show how just the single parameter of the injection rate changes are/can be linked to any anomalies to alert operators of any type of potential leak from the well. No cited publications for this specific linkage or theory. Shouldn't there be literature review of linkage and not just of modeling in the paper?
Authors response: We thank the reviewer for this response. It is observed from the data that a single delta injection parameter is intricately linked to the responses of multiple sensors deployed both laterally and vertically. Our methodology integrates data from these sensors to derive the single parameter, which serves as a key indicator of anomalous behavior in the system.

   While our literature review has primarily focused on the modeling aspects of our research, we recognize the importance of providing context on the linkage between injection rate changes and leak detection. To address this, we have expanded our literature section to include relevant publications that discuss the theoretical underpinnings and empirical evidence supporting this linkage.

   Furthermore, we would like to clarify that this area of research is novel, as stated in our literature review. Lastly, we would like to note that none of the other three reviewers raised this specific issue, which may suggest that the concern raised could stem from a misunderstanding or lack of familiarity with the intricacies of our research methodology.

c. In highlights: Predicting this change can be used to provide a checkpoint against carbon plume migration and can determine if there are losses in the injection process. Not shown or explained in this paper on how knowing an injection rate can tell one about plume migration of CO_2 or injection well integrity.

Authors response: We thank the reviewer for this response. We think it will be hard to disagree with our view that changes in injection rate are an effective means to monitor the behavior of the injection process over time. But we are trying to extend this analysis further and determine whether we can find a way to link changes in injection rates to potential issues such as leaks or changes in reservoir behavior. By detecting deviations from expected injection patterns, operators can investigate further to determine the root cause of these anomalies, which may include integrity issues with the injection well or unwanted migration of CO_2.

Secondly, while the paper primarily focuses on predicting injection rate deltas using machine learning techniques, it should be part of a larger framework for monitoring and managing CCUS operations. In practice, the predictive model would be integrated into a comprehensive monitoring and control system that includes real-time data from various sensors, geological monitoring, and reservoir simulations. By combining information from multiple sources, operators can gain a holistic understanding of the injection process and make informed decisions to ensure the safe and efficient operation of CCUS projects.

d. Permit requires monitoring the injection well annulus pressures and periodic casing pressure tests and the use of reservoir saturation tool in the cased hole to try and detect CO_2 outside of the casing.

Authors response: We appreciate the reviewer's emphasis on the importance of existing monitoring methods such as annulus pressure monitoring, casing pressure tests, and the use of reservoir saturation tools. These approaches are indeed fundamental for ensuring the integrity and safety of injection wells in CCUS projects. In fact, the machine learning (ML) model uses some these parameters as inputs.

It's important to note that the ML method proposed in our study serves as an additional layer of monitoring and analysis, complementing these existing techniques. While traditional methods provide valuable real-time data and direct measurements, ML offers the potential to analyze large volumes of historical data, detect subtle patterns or anomalies, and predict future trends.

Moreover, we acknowledge the potential for ML to optimize operational expenses (OPEX) by reducing the frequency of certain tests or enabling more targeted monitoring strategies. By leveraging ML algorithms to identify trends and anomalies in the data, operators can make informed decisions about when and where to deploy traditional monitoring techniques, thereby maximizing their effectiveness and minimizing unnecessary costs.

We recognize the importance of integrating ML methods with established monitoring protocols and hardware-based tools to create a comprehensive and robust monitoring framework for CCUS projects. This synergy between empirical methods and data-driven analytics can enhance the overall safety, efficiency, and cost-effectiveness of carbon capture and storage operations.

2. If applicable, is the application/theory/method/study reported in sufficient detail to allow for its replicability and/or reproducibility?

Please provide suggestions to the author(s) on how to improve the replicability/reproducibility of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3: Mark as appropriate with an X:
Yes [] No [X] N/A []
Provide further comments here:

e. There is great detail of information on building the model, which in this case is built on training data that the authors' unsuccessfully attempted to "clean up" the not understood problems with the raw recorded parameter data. Part of the problem also centers around the understanding of basic hydrostatic formation pressures for the verification well data – there can't be zero formation pressures.
   Authors response: We find this response a bit puzzling, because there are no zero values in the selected model as indicated in Table 4. We, in fact, describe how the zero values are handled. We utilize many different methods (forward or backward fill, dropping the rows with zero values), but for the sake of paper length, only document the final method we employ which is the forward fill method.

   To the reviewers second point about values that are lower than formation pressure, we agree that the more correct method is ensure that there are no values below the formation pressure at the sensor depth. We have handled this via an additional step in the data cleaning stage (lines 213-214 in the revised manuscript).

---

3. If applicable, are statistical analyses, controls, sampling mechanism, and statistical reporting (e.g., P-values, CIs, effect sizes) appropriate and well described?

Please clearly indicate if the manuscript requires additional peer review by a statistician. Kindly provide suggestions to the author(s) on how to improve the statistical analyses, controls, sampling mechanism, or statistical reporting. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3: Mark as appropriate with an X:
Yes [] No [X] N/A []
Provide further comments here:

f. There are nearly no details on where the 11 pressure/temperature sensors are in the verification well and how the pressures were impacted by the baffles in the Mt. Simon in relation to the injection zone!
   Authors response: Noted and this has now been addressed in the paper.

g. No explanation on why the only Z05 (Zone 5) pressure/temperature sensor of the verification well was picked for the learning data. Zones 4-9 are above the baffles and are in a part of the aquifer that reacted very little to injection well pressures changes. For Zone 5, with a very, very slow buildup of the 25 psi pressures, took 3 years. It also took 100+ hours to see pressure changes at Z05 following

changes in injection while sensors at other elevations below the baffles had increases of 169 psi and 1 hour to see pressure changes.
Authors response: Our approach hinges on analyzing deltas, parameter changes, and trends rather than absolute values. As indicated in the correlation matrix presented in the paper, the time series trends from sensors in the verification well are highly collinear. This implies that including additional sensors from these zones would offer limited value in terms of enhancing the predictive capabilities of the model.

Moreover, sensitivity runs were conducted, as detailed in the "Sensitivity Runs" section, to explore various combinations of downhole sensors. These analyses further supported the decision to focus on the Z05 sensor. While we acknowledge that the different rates of pressure buildup across zones may reflect variations in reservoir properties that could impact storage volume, addressing such nuances falls outside the scope of our study. Our primary goal is to detect deviations from expected behavior and identify potential containment issues.

h. Pressure readings through the 3 years of injection are shown in diagrams in several publications to give an overall bounds for some of the “clean up” parameters without directly going through the raw data in detail to find: pressure values below original formation pressures (which includes 0), injection well head pressure values above permitted and equipment capable highs, remove pressure changes after sensor re-installation that had jumps in pressure readings until sensors were re-installed again, pressure values stuck at one value for long periods, major time gaps (up to 3 months), and negative null values.
Authors response: We have now addressed this issue by incorporating these bounds as an additional layer of data cleaning process.

i. Forward fill of pressure values in verification well data that are associated with very reactive sensors and high pressure changes for some times gaps which are as long as 3 month, would produce fairly fictitious values!
Authors response: There is no perfect method to deal with missing data; this is why experience matters. As authors, we have carefully monitored the data to make sure such a scenario does not occur; we exclude the data if it does.

j. Text says 6 of the 33 parameter variables were used in the model and site Table 2 for the variable. Table 2 has 9 variables, and the two paired temperature/pressure were to only use one of the values – which ones were used and that makes 7 variables that were used?
Authors response: There were 33 parameters to begin with, after data-cleaning and checking co-linearity, this was reduced to 8 excluding the target injection delta. This has been updated in the paper.

k. Parameters such as in table 1 probably should be described what they represent. What is inj-diff and its units?
Authors response: This is now included in the nomenclature table in the appendix.

l. Why isn’t the hold out data modeled injection rate changes shown? Figure 8 covers the time period when the injection rate was at it maximum of 42 to 44 tonnes/hr rate and there were two 0 injection time periods of 10 hours on the 20th and 3 hours on the 26th.
Authors response: We attempted to show the anomalies predicted by the injection pressure deltas and then based on that investigate the sensor parameters. We agree that showing the holding dataset is valuable and have now included it in the paper.

m. Figure 5 for b Check file of small subset of data. The injection rates were at the typical 42-44 TPH rate which is a typical fluctuation range for that entire time period of b.
Authors response: Noted; thank you for the comment. It's important to clarify that our analysis primarily focuses on detecting anomalies and changes in data trends rather than absolute values. As such, the small fluctuations in injection rates, while within the expected range, still could contribute valuable information or rather this work is to determine if it does.

---

4. Could the manuscript benefit from additional tables or figures, or from improving or removing (some of the) existing ones?

Please provide specific suggestions for improvements, removals, or additions of figures or tables. Please number each suggestion so that author(s) can more easily respond.

Reviewer #3:

n. Tables have data problems and no explanation of some of the data: . Table 4; What is the VW DH Sensor? Pressure or temperature? What is the Temp Sensor? VW Zero Value – there should be NO zero values for temperature or pressure.
Authors response: This has now been addressed in the paper as per the above.

o. unless the authors converted the times to UTC, all the time data is local time.
Authors response: Noted and amended.

p. Explain what is in the tables and figures. Explain what are the parameters in table 1 and 2 and the colored boxes in figure 8 – as examples.
Authors response: This has been edited and the figure changed in the paper.

q. In table 8, do not know what is real input data and what is the predicted values. For Avg_CCS1_DH6325Ps_psi, the raw recorded data is all below 3300 psi with a short downward change of 230 psi on the 20th and 162 psi on the 26th. Doesn't match the data in table 8.
Author: Figure 8 has the incorrect dates; this has now been updated and it has been verified that there is no change in analysis. The raw recorded data for Avg_CCS1_DH6325PS_psi should correspond to the dates 20 Nov 2014 to 26 Nov 2014.

---

5. If applicable, are the interpretation of results and study conclusions supported by the data?

Please provide suggestions (if needed) to the author(s) on how to improve, tone down, or expand the study interpretations/conclusions. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3: Mark as appropriate with an X:
Yes [] No [X] N/A []
Provide further comments here:

r. Results for the success of the model was to run 67% of the data to teach the model and use the 33% held back data to run to predict injection rate changes. I believe this was supposed to be accomplished in Figure 8 which has no legend for viewer to figure out which data is which. Couldn't the predicted parameters be compared to the actual measured parameters of injection rate? Which is not in the graph! Visually it would be nice to see that data as a comparison and not a derivative of the data. 19. No results or explanation given for linking injection rate changes to containment issues.
Author: Noted and Ground Truth values have now been added to the paper.

---

6. Have the authors clearly emphasized the strengths of their study/theory/methods/argument?

Please provide suggestions to the author(s) on how to better emphasize the strengths of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #3:

s. Hard to come up with a strength when study/theory cited in the title is so incomplete. Question the use a complicated Artificial Intelligence based Time-Series Prediction to predict injection rate changes using Well head injection pressure and temperature, annulus pressures, down hole pressures and temperatures, and two variables from the verification well 1007 feet away, when simple relationships can be examined and developed between just several of the injection well parameters without AI.
Authors response: While simple relationships between some injection well parameters can indeed be examined and developed without AI, our methodology offers distinct advantages in capturing nuanced patterns and interactions within the data that may not be readily apparent through traditional analyses. Furthermore, our aim is not solely to predict absolute values but rather to analyze deltas, changes, and trends in the data. For instance, consider the relationship between injection rate changes and pressure variations. This approach allows us to identify anomalies and trends that could indicate potential issues or opportunities for optimization.

While it's true that simpler analyses can be conducted for individual wells, the scalability of such methods becomes a significant challenge when dealing with a large number of wells. In contrast, Machine Learning and AI offer the capability to analyze vast quantities of data from numerous wells simultaneously, enabling operators to prioritize interventions based on predictive insights. For example, if there are thousands or even millions of wells in a field, AI-driven analytics can help identify the most critical areas requiring attention, thereby optimizing resource allocation and operational decision-making.

Lastly, this is a prototype, a start which is why we are using such a dataset that is simple, known and one can easily derive the expected result as pointed out by the reviewer to see what the model does and see how well it does, what breaks the model, etc. The aim would be to scale this to more challenging situations and inputs.

---

7. Have the authors clearly stated the limitations of their study/theory/methods/argument?

Please list the limitations that the author(s) need to add or emphasize. Please number each limitation so that author(s) can more easily respond.

t. Reviewer #3: None stated.
Authors response: We acknowledge that while we may not have explicitly labeled them as 'limitations' in our paper, we have indeed addressed areas for improvement within our model. These include dealing with outliers/garbage values effectively, including a feedback loop and reduction of runtime optimization. These suggestions inherently represent limitations that need to be addressed in future iterations of this work.

---

8. Does the manuscript structure, flow or writing need improving (e.g., the addition of subheadings, shortening of text, reorganization of sections, or moving details from one section to another)?

Please provide suggestions to the author(s) on how to improve the manuscript structure and flow. Please number each suggestion so that author(s) can more easily respond.

Reviewer #3: Structure is not a problem

Authors response: Noted; thank you

---

9. Could the manuscript benefit from language editing?

Reviewer #3: No

Reviewer #3:

u. main points: As stated in line 412 & 413 of the Conclusion, the model was made to predict the injection rate changes of the CO_2 injection. And lines 418 & 419 state that the model's primary objective is to detect anomalies and alert operators to closely inspect the well for potential leaks. Using predicted parameters to validate CO_2 containment in the Well - title. In highlights: Predicting this change can be used to provide a checkpoint against carbon plume migration and can determine if there are losses in the injection process. Not shown or explained in this paper on how knowing an injection rate can tell one about migration of CO_2 or injection well integrity.
Authors response: Noted; we have edited where we can

v. Line 62 Mt. Simon Sandstone is the official name. Not Mount.

Authors response: Noted; edited

w. Line 66 Injection started in Nov 2011 not 2009. Drilling was in 2009.
Authors response: Noted; edited

x. Line 67 the distance between the Injection well and Verification well is 1007 ft as shown in Bauer et al. 2016.
Authors response: Noted; edited

y. Line 79 What are the other losses?
Authors response: Noted; edited. We are referring to downhole losses, such as casing leaks, thief zones etc. Some of these changes are small, and conventional logging tools may not be able to detect them.

z. Line 81 Do not understand how knowing injection rate changes, tells one the integrity of the well. Permit requires monitoring the injection well annulus pressures and periodic pressure tests and the use of reservoir saturation tool in the cased hole to try and detect CO_2.
Authors response: Noted; periodic pressure tests, and use of logs implies an OPEX; a ML method is complimentary to these methods but can help lower costs for the operator by reducing the frequency such operations are conducted. We also want real-time monitoring; the methods recommended by the reviewer are not real-time.

Regarding the understanding of injection rate changes, they serve as indicators of potential anomalies in well behavior. For instance, a sudden change in injection rate, when all other parameters remain constant, could signal an issue that needs attention, such as a breach in containment. Therefore, our method aims to provide valuable insights into well integrity by analyzing these changes and identifying potential anomalies.

aa. Line 94 hydrocarbon and water rates - RECOVERY? Rates
Authors response: Noted; edited.

bb. Line 124 Data was - data is plural - Data were
Authors response: Noted; edited.

cc. Line 133 Illinois Basin - Decatur Project hypen missing
Authors response: Noted; edited.

dd. Line 136 checkpoint against carbon migration. Authors are not working with any data showing where the CO_2 is or was located and how a single parameter of injection rate is a checkpoint for understanding CO_2 migration.
Author: the focus of our paper is on developing a machine learning model to serve as a tool for monitoring well integrity and CO_2 containment. While understanding the exact location of CO_2 migration is valuable, it falls outside the scope of our current study. The purpose of our model is to detect anomalies in parameters such as injection rate, which could indicate potential issues such as casing-tubing communication failure or reservoir saturation. These anomalies serve as checkpoints for operators to further investigate and take appropriate actions to ensure well integrity and CO_2 containment.

ee. Line 139 modelling variation in well and storage parameters to validate CO2 containment. Of all the dynamic parameters, which are indicators or are associated with CO2 containment and what is the definition for this? Or even where the CO2 is located - CO2 plume?
Authors response: Noted; edited.

ff. Line 142 No details on the annulus monitoring and nearly no details on where the sensors are located in the verification well and how the pressures were impacted by the baffles in the Mt. Simon in relation to the injection zone!
Authors response: Noted; but is this relevant to proving a ML model works? This paper is not meant to discuss the geologic metrics of the measured data. As explained earlier, we are accepting the data as is, and developing a method to help engineers detect anomalies. And even though there are baffles, pressure data indicates hydrostatic communication, and all sensor trends are highly co-linear.

gg. Line 145 TD of injection well is 7238 ft as shown in ref. 3.
Authors response: Noted; edited.

hh. Line 149 proper name is Precambrian
Authors response: Noted; edited.

ii. Line 153 Mt. St Simon delete St
Authors response: Noted; edited.

jj. Line 163 There are other problems in the data: Also pressure values stuck at one value for long periods, major time gaps (up to 3 months), in monitoring during removal of sensors, negative null values.
Authors response: Noted; All these values have been dealt with during the data cleaning process. There are no negative values, no null values. We use multiple inputs to the model in order to mitigate the frozen values. This will be treated as an improvement and has been indicated in the paper.

kk. Table 1 shows some of the data problems. Max value for WHCO2Inj of 39,032 psi - permit and the equipment limits are 2,380 psi.
Authors response: This is a comment and well noted. Table 1 is the raw value. Table 2 is the cleaned value which has now been incorporated to include the reviewer's comment.

ll. Line 171 (i) Would think that the first task for cleaning up the data would be to remove significant outliers, values below original formation pressures (which includes 0), injection well head pressure values above permitted and equipment capable highs, remove pressure changes after sensor re-installation that had jumps in pressure readings until sensors were re-installed again, then do forward fill for some times gaps which are as long as 3 month! This method has many pitfalls without going through the entire data set in detail and determining even small outliers, especially if you are working with only a 25 psi change in 3 years for Z05. Zone 5 was above a set of baffles in the Mt. Simon formation and the injection was below the baffles, resulting in a very slow 25 PSI increase over 3 years of injection with 100+ hours delay in pressure communication between the Injection well and the Z05 sensor. Data needs detailed visual screening.
Author: The data cleaning process now incorporates the reviewer's comment. As for the choice of sensor, the point here is there is pressure communication. Z05 sees the change albeit small. And the data shows that the Z05 and the other sensors are highly correlatable. That is, changes detected in the other sensors are also being detected in Z05. We ran sensitivities with other sensors, Z1, Z2 and Z3

and there is no major impact to the model's objective. As we are dealing with deltas, this is captured and Z5 was picked purely based on the lowest RMSE value.

mm. Table 2. Cleaned up data: VW1_Z05: minimum value of the measured formation pressure can not be lower than the original formation pressure. There is no withdrawal of formation waters to lower it! The original formation pressure for Zone 5 was 3051.8 psi. Going through the data in detail for Zone 5 data, one is looking for changes outside of this overall 25 psi change over 3 years. The median value in Table 2 is at the maximum pressure of about 3076 after 3 years. These values in this table for Z05 show the problems with this data to be easily cleaned up with the method used.
Author: This has now been addressed as per previous responses.

nn. Table 2. Cleaned up data: CCS1 well head injection pressures should be cleaned up so that permit required maximum levels of pressure (2,380 psi) and rate are the maximum values. These permitted maximum values are also near the equipment and pipeline maximum operating pressures.
Author: This cleanup now been addressed as per previous responses. But we would like to point out that it does not necessarily mean all operators adhere to the permitted wellhead injection pressures.

oo. For all the diagrams with time. The original data is in local time not UTC - unless authors have converted it.
Author: Noted. Thank you.

pp. Line 342 Table 4 are the listings of input parameters in the model to test predicted output of the other parameters and as stated authors are predicting the changes in the injection rates by using other recorded contemporaneous data. Final model run has input of injection well head pressure, which can be related to volume from a project developed relationship and volume over time is injection rate. Why the complicated model then?
Author: Indeed, the final model includes input parameters such as injection well head pressure, which can theoretically be directly related to injection volume over time. However, the complexity of the model arises from its ability to capture nuanced relationships and detect anomalies that may not be apparent in straightforward correlations. For instance, while changes in injection well head pressure may directly influence injection rates in conventional scenarios, there could be instances where changes in other variables, not directly tied to well head pressure, impact injection rates.

Regarding the possibility of changes in injection rates without corresponding changes in well head pressure, while it may seem counterintuitive, it's conceivable in certain operational contexts. For instance, changes in downhole conditions, reservoir characteristics, or equipment performance could potentially influence injection rates independently of variations in well head pressure. Therefore, the model's complexity allows for the identification of such nuanced patterns and anomalies, providing a more comprehensive understanding of system behavior beyond simple correlations.

qq. Table 4; What is the VW DH Sensor? Pressure or temperature and which one? What is the Temp Sensor? VW Zero Value - there should be NO zero values for temperature or pressure.
Author: Thank you for pointing out the ambiguity. The VW WH DH Sensor refers to the pressure sensor. The table in the report has been amended. As for the zero values, this has now been addressed as per responses above.

rr. Figure 8. What are the different colored boxes? Don't understand the flat line data for Z05 from 20 Nov 2012 through about 24 Nov 2012. Pressures during this time period fluctuated from 3069.079 to 3069.65 psi and outside of it not being flat data, it doesn't even match the 3071.5+ values in this

graph, which are in 0.1 divisions and should show the raw data fluctuation range or that there are problems with the data clean up method.
Author: We have replacedFigure 8; we hope the results are clearer to the reviewer

ss. References 3, Authors need corrections and Illinois Basin-Decatur Project - needs caps.
Authors response: Noted; edited.

tt. References 10, 15, and 17 need authors fixed.
Authors response: Noted; edited.

uu. If verification well data is used for predictions, one may want to use data from zones that were rapidly affected by pressure changes at the injection well. Zones 1 through 3 are below a baffle that affected injection transmitting changes in formation pressures in the Mt. Simon and are near the level of the CCS1 injection and reacted to CCS1 changes within about an hour and had maximum recorded pressure changes of 169 psi. Zones 4-9 are above the baffles and are in a part of the aquifer that reacted very little to pressures changes. For Zone 5, the very, very slow buildup of the 25 psi pressures took 3 years. Once when the sensor was pulled and reset, it took 5 months for it to restabilize to the original pressures.
Authors response : Our approach hinges on analyzing deltas, parameter changes, and trends rather than absolute values. As indicated in the correlation matrix presented in the paper, the time series trends from sensors in the verification well are highly collinear. This implies that including additional sensors from these zones would offer limited value in terms of enhancing the predictive capabilities of the model.

Moreover, sensitivity runs were conducted, as detailed in the "Sensitivity Runs" section, to explore various combinations of downhole sensor. Z05 is the best option in terms of RMSE which is how a LSTM ML model is evaluated on. While we acknowledge that the different rates of pressure buildup across zones may reflect variations in reservoir properties that could impact storage volume, addressing such nuances falls outside the scope of our study. Our primary goal is to detect deviations from expected behavior and identify potential containment issues.

Response to Reviewer #4:

Thank you for your feedback. We have made the revisions requested to the manuscript and addressed your comments in this document in blue. We hope this adequately addresses the concerns raised.

To the editor, here are our responses/explanations based on the email:

International Journal of Greenhouse Gas Control
Reviewer's Responses to Questions

Note: In order to effectively convey your recommendations for improvement to the author(s), and help editors make well-informed and efficient decisions, we ask you to answer the following specific questions about the manuscript and provide additional suggestions where appropriate.

1. Are the objectives and the rationale of the study clearly stated?

Please provide suggestions to the author(s) on how to improve the clarity of the objectives and rationale of the study. Please number each suggestion so that author(s) can more easily respond.

Reviewer #4: Yes. See detailed comments for additional input.

Author Response: Noted, Thank you. We will address your comments in the "Detailed comments" section below

---

2. If applicable, is the application/theory/method/study reported in sufficient detail to allow for its replicability and/or reproducibility?

Please provide suggestions to the author(s) on how to improve the replicability/reproducibility of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #4: Mark as appropriate with an X:
Yes [x] No [] N/A []
Provide further comments here: See detailed comments for additional input.

Author Response: Noted, Thank you. We will address your comments in the "Detailed comments" section below

---

3. If applicable, are statistical analyses, controls, sampling mechanism, and statistical reporting (e.g., P-values, CIs, effect sizes) appropriate and well described?

Please clearly indicate if the manuscript requires additional peer review by a statistician. Kindly provide suggestions to the author(s) on how to improve the statistical analyses, controls, sampling mechanism, or statistical reporting. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #4: Mark as appropriate with an X:
Yes [x] No [] N/A []
Provide further comments here: See detailed comments for additional input.

Author Response: Noted, Thank you. We will address your comments in the "Detailed comments" section below

---

4. Could the manuscript benefit from additional tables or figures, or from improving or removing (some of the) existing ones?

Please provide specific suggestions for improvements, removals, or additions of figures or tables. Please number each suggestion so that author(s) can more easily respond.

Reviewer #4: No. Would only suggest clarifying the existing ones, as described in the detailed comments section.

Author Response: Noted, Thank you. We will address your comments in the "Detailed comments" section below

---

5. If applicable, are the interpretation of results and study conclusions supported by the data?

Please provide suggestions (if needed) to the author(s) on how to improve, tone down, or expand the study interpretations/conclusions. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #4: Mark as appropriate with an X:
Yes [] No [x] N/A []
Provide further comments here: As presented, the figures and text do not have enough stand-alone information to support the conclusions. See detailed comments for suggested improvements to improve clarity.

Author Response: Noted, Thank you. We will address your comments in the "Detailed comments" section below

---

6. Have the authors clearly emphasized the strengths of their study/theory/methods/argument?

Please provide suggestions to the author(s) on how to better emphasize the strengths of their study. Please number each suggestion so that the author(s) can more easily respond.

Reviewer #4: Yes. See detailed comments for additional input.

Author Response: Noted, Thank you. We will address your comments in the “Detailed comments” section below

---

7. Have the authors clearly stated the limitations of their study/theory/methods/argument?

Please list the limitations that the author(s) need to add or emphasize. Please number each limitation so that author(s) can more easily respond.

Reviewer #4: Somewhat. The authors clearly describe their methods, which is refreshing. They clearly describe what it can do, but a balanced approach may be in order to better describe some of the method's limitations.

Author Response: Noted, Thank you. We will address your comments in the “Detailed comments” section below

---

8. Does the manuscript structure, flow or writing need improving (e.g., the addition of subheadings, shortening of text, reorganization of sections, or moving details from one section to another)?

Please provide suggestions to the author(s) on how to improve the manuscript structure and flow. Please number each suggestion so that author(s) can more easily respond.

Reviewer #4: No.

Author Response: Noted, Thank you. We will address your comments in the “Detailed comments” section below

---

9. Could the manuscript benefit from language editing?

Reviewer #4: No

Author Response: Noted, Thank you. We will address your comments in the “Detailed comments” section below

Reviewer #4:

1. Line 41. To improve clarity, remove the word "only".
   Author Response: Edited; we have removed the line based on comments from reviewer #1

2. Reference 1. Although from a reputable source, this reference is only pointing to a news article. Especially for your first citation, I would encourage a more rigorously scrutinized source. Is there also a peer-reviewed source that contains the same information?
Author Response: Edited; we have added a new source.

3. Line 44. Coal, oil and natural gas are the largest used sources of fossil fuels, but not the only ones. Similarly CO_2, CH_4, and N_2O are the largest produced GHGs, but not the only ones. Clarify language by modifying text to read: "The burning of fossil fuels (such as coal, oil, and natural gas) has resulted in the generation of various GHGs, such as carbon dioxide (CO_2, methane (CH_4) and nitrous oxide (N_2O).
Author Response: Edited; thank you

4. Reference 2. Please update reference, preferably to a report or peer-reviewed journal. Reference 2 is pointing to an online webpage from a reputable source that was last updated on 23 February 2024. The webpage does not indicate that the amount of CO_2 generated in 2020 to be ~3.11 million metric tons.
Author Response: Edited; we have added a new source.

5. Line 53. CO_2 storage can be carried out in a number of different ways, not just the 3 listed. Clarify language by modifying the text to read: "CO_2 geologic storage can be carried out in a number of different ways, including via injection into …"
Author Response: Edited; thank you

6. Line 60. This paragraph requires the addition of peer-reviewed journal references.
Author Response: Edited; we have removed the line based on comments from reviewer #1

7. Reference 3. The reference author names and format need to be corrected for this and other references. For this particular reference, correct reference information: "Bauer RA, Will R, E. Greenberg S, Whittaker SG. Illinois Basin-Decatur Project. In: Davis TL, Landrø M, Wilson M, eds. Geophysics and Geosequestration. Cambridge University Press; 2019:339-370."
Author Response: Edited; thank you

8. Line 73. Here and elsewhere, clarify "carbon capture well" terminology. I believe you mean "capture sequestration well", as opposed to something to do with the carbon capturing process itself.
Author Response: Edited; thank you

9. Introduction section. A discussion should be added about CO_2 injection rates in general, what drives them, and why their calculation is a somewhat difficult problem for CO_2 sequestration. Of deep interest is the calculation of the maximum rate at which CO_2 can be injected into the subsurface by human operators. We are interested in the maximum rates of course because current climate models suggest that rather large amounts of CO_2 injected at high rates is needed to sequester CO_2 as fast as possible to mitigate climate change. Given that operators may want to have as high a rate as possible, what are the factors that actually determine the rate at which the operators are injecting CO_2 (e.g., the pressure rise in the aquifer, equipment malfunctions, etc)? This would be directly relatable to what you are predicting. Lastly, there should be a discussion about why AI can become a preferred method: among other things, some existing methods to estimate subsurface injection rates can become complex and/or costly when considering at a basin scale. I'm sure there are other reasons that can be stated as well. What are the other ways in which maximum injection rates are currently calculated? What are the tradeoffs in methods? There is often, no single right way of doing things.

Author Response: A paragraph with regards to optimum CO2 injectivity has been added. In summary, achieving optimum CO2 injectivity relies on various factors, including geological and reservoir properties such as permeability and heterogeneity, effective pressure management, maintenance of injection fluid properties, and appropriate pump and well design. The goal is to determine the injection rate that maximizes volume over time while ensuring the storage reservoir's capacity is not exceeded. This emphasis on optimum rather than maximum injection rate considers the need for sustainable CO2 sequestration. Injecting too rapidly can lead to issues like premature reservoir filling or skin problems, reducing injectivity. Insights and methodologies from the oil and gas industry, such as nodal analysis, can inform our approach. However, further discussion on this topic falls outside the scope of this paper.

10. Line 94. Clarify text: "Within reservoir engineering, the prediction of hydrocarbon and water production rates from geological …"
Author Response: Edited; thank you. This statement simply means that predicting flow rates are a time series problem where future rates are predicted based on historical rates.

11. Equation 2. The text in Lines 95-99 seems to indicate that Equation 2 is discussed in Reference 14. However, this equation is not included in Reference 14, Arps (1945). Additionally, there appears to be mathematical issue with this equation since one option has b=0, but then the exponent 1/b would be 1/0, which is impossible to answer since division by zero is undefined. This equation should be corrected, correctly referenced, each variable should be defined and units stated (including t).
Author Response: Edited; thank you. The reviewer is incorrect; these equations are present in Pg 19, table 5. We express all 3 forms of the equation in the table and expand the explanation to include the range of values of b for each equation.

12. Line 118. This sentence is misleading. In the field of CCUS, there are currently well over 100+ fields with data collected. Additionally, "injector production" is confusing as well: An injection well adds fluid to the subsurface, but a production well removes fluid from the subsurface. Which is meant by this term? In general I would say that data has been collected (although data itself is sometimes difficult to share, which is a different issue.) Even in the ML realm, Reference 23 states "ML algorithms have been widely used in CCS research and achieved good effect…". The beginning of this paragraph should be re-written to be in line what the references show as well.
Author Response: Edited; thank you. We have replaced the word “injector production” with “well” performance. We have rewritten the paragraph slightly.

13. Line 123. The Iskander et al sentence is missing the reference number.
Author Response: Edited; thank you

14. Table 1. A description of what the 34 measurements are is needed. For example, what is "Avg_PLT_CO2VentRate_TPH" actually measuring and what are the units? The short names are sometimes not very descriptive. Also, what does "Non-Zero Value" mean?
Author Response: We have edited the and address this in the nomenclature table.

15. Line 212. Another plus of LSTMs are that they are "effective at capturing long-term temporal dependencies without suffering from the optimization hurdles that plague recurrent networks", right? (Greff et al., 2015)
Author Response: Reference has been included; thank you

16. Figure 4. Y-axis appears to be truncated. Colorbar needs descriptor.
    Author Response: Edited; thank you

17. Line 270. Why were these 6 variables in particular retained?
    Author response: Many variables exhibit strong correlations, with coefficients exceeding 0.5 (See correlation matrix). To prevent multicollinearity issues, we retained only one variable from each group of highly correlated variables. Exceptions were made when variables originated from different sources, such as tubing and reservoir pressure at the observation well. Excluding the target injection delta variable, we selected eight variables for the machine learning application.

18. Figure 5. What is the y-axis with units on 5b?
    Author response: tonnes per hour. Figure amended.

19. Figure 5 and 6. The 5b and 6b close up comparisons between the actual and LSTM predictions do not match up well. There should be some discussion about why this is okay (or not). Are the larger amplitude variations of greater interest in a real-world setting and is your model capturing those wiggle-for-wiggle? (Can't tell from the figure.) Are these smaller scale variations not of importance in a real-world setting? Is further decimation of the data necessary and/or useful?
    Author Response: Fig 5 is just showing one example from a K-fold. It's a smaller data set, so the match will be poorer, but the model uses these numerous small data sets to ultimately tune the large scale macro model.

20. Line 318. How are you defining an anomaly? How is this useful in a real world example?
    Author Response: In a CO2 injection project, we anticipate maintaining a consistent optimum injection rate and injection pressure – therefore we define an anomaly as anything that disrupts the equilibrium seen in past measurements.

21. Table 4. A description of the Varied Parameters is needed. For example, what does "Z-Score Inj_Diff" actually mean? This actually appears to be two tables stitched together, they should be separated and separately described.
    Author Response: Noted; we have split the table as requested although we think it makes for a less impactful presentation. We have explained what Z-score means in "Nomenclature"; its just a conventional statistical measurement, like mean or mode.

22. Table 5. Table 5 appears to be truncated. No column headers. Cannot evaluate.
    Author Response: Noted; it is not truncated. We have added a new column header (there was a previous header there already) – we hope this is clearer

23. Figure 7. The comparisons do not appear to match up well even though the authors indicate that "all results show small perturbations around the unseeded value". There should be some discussion about why variations up to an order of magnitude difference is okay (or not).
    Author Response: We remind the reviewer that the expectation that the results match perfectly when initial conditions change is an unreasonable one to make. Of course, the results will be different. What we want to demonstrate is that it is insensitive to initial seed values because results only change within +/- 10% of a base (unseeded value) case. We are measuring at fractions of a psi, after all.

24. Figure 8. Units needed on y-axis. X-axis units are unclear, is this days? What do the yellow and green boxes represent? Where are the four anomalies described in the text?
    Author Response: This figure is replaced with something that we hope is clearer.

25. Line 418. Your motivation is important and should also be stated in the introduction to better emphasize the strength of your technique.
    Author Response: Noted; we have emphasized this again in the introduction and conclusion.

26. Conclusions. How would a significant equipment failure (or similar event) in the training dataset be represented? Would the data need to be cleaned, or would it be able to cope? What if there was such a failure in the testing dataset? In an operational example? What would happen?
    Author Response: Equipment failure can indeed lead to anomalous readings in the sensor data. For instance, if the pump malfunctions, it would likely affect the injection well's wellhead pressure, which in turn would be detected by the downhole sensors. The model would recognize this deviation from the normal operating pattern as an anomaly, prompting operators to investigate and address the issue promptly. Moreover, such anomalies serve as indicators that the containment of CO_2 is intact, providing assurance of safety and operational integrity. On the other hand, if there is a failure in the wellbore, the anomaly would likely manifest in the nearest sensor of the injection well. However, there may not be corresponding changes in the injection pressure or other sensors in the well. Nonetheless, this anomaly would still trigger an alert regarding the injection delta, signaling operations to investigate further. Once confirmed, actions such as shutting in the well and initiating wellbore repair procedures would be taken promptly to maintain operational efficiency and prevent any potential environmental or safety concerns.

Highlights

- CCUS is one method to deal with produced CO_2.
- Prediction how the CO_2 behaves in the subsurface once injected is difficult.
- We aim to use LSTM neural networks to predict injection deltas, which are changes that occur during the injection process.
- The input data source comprises measurements taken from sensors located a distance away in a monitoring well.
- Predicting this change can be used to provide a checkpoint against carbon plume migration and can determine if there are losses in the injection process.

Title: Utilisation of Artificial Intelligence based Time-Series Prediction to validate Carbon Containment in Injection Well in Illinois Basin

Authors: Munish Kumar[a] and Kannappan Swaminathan[b]

Affiliations: [a]Singapore University of Social Sciences, School of Business, Clementi Rd, #463号, Singapore 599494

[b]Insights Inc

Corresponding author. Email: munishkumar001@suss.edu.sg

Abstract:

This paper focuses on using time series injection data and monitoring information to predict changes in injection rates for the carbon sequestration well. The data we have used comes from the Illinois Basin - Decatur Project, a pilot CO_2 project that demonstrated the practical feasibility of storing CO_2 underground. The injection spanned three years, during which nearly 999,215 tonnes of CO_2 was stored. Data was recorded across a pair of wells equipped with sensors to track pressure and temperature at various depths.

We perform the prediction using Long Short-Term Memory (LSTM) neural networks (NN). These changes, represented as deltas (Δ or inj_diff) in injection rates between time t and time (t-1), are crucial indicators of carbon containment within the well. By correlating these rate changes with other well parameters, this approach serves as a checkpoint against unwanted and unexpected carbon containment breaches or downhole losses during the injection process.

Our work aims to show that machine learning methods can be useful to forecast these injection rate deltas based on monitoring data, thereby providing a way that is complimentary to traditional methods, to determine the effectiveness of carbon containment during injection.

One-Sentence Summary: Applying machine learning and predictive analytics via time series injection information and monitoring data on a carbon sequestration well to predict well injection rate deltas.

Keywords (minimum 6): low-carbon, time-series, neural network, LSTM, carbon capture, injection pressure, monitoring, migration

Introduction

The burning of coal, oil, and natural gas has resulted in the generation of various greenhouse gases such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) [1]. A report generated Liu et al revealed that global CO_2 emissions for 2022 reached 36.1 $GtCO_2$ [2]. Failure to effectively manage such substantial quantities will result in irreversible environmental consequences.

Carbon Capture Utilisation and Storage (CCUS) is one promising method to deal with the produced CO_2 from anthropogenic sources. The idea is to capture CO_2 from an emission point source and subsequent sequester it via injection into a suitable geological formation, with the explicit aim to store the CO_2 safely, in a state of permanence. CCUS is now being viewed as a key technology that will assist us in reaching increasingly ambitious global anthropogenic climate change goals. Typically, CO_2 geologic storage can be carried out in a number of different ways, including Enhanced Oil Recovery (EOR) processes, injection into virgin saline aquifers or into depleted oil and gas fields. These methods all have different project drivers, risks, and commercial implications. However, what these three methods have in common is the requirement that (a) there be a good understanding of the subsurface geological properties and (b) there be some ability to monitor and even predict CO_2 containment behaviour at the well scale, be it during the injection phase or during the shut-in phase.

The importance of real-time CO_2 containment monitoring in the subsurface

Evaluating CO_2 containment is a multiscale challenge, with measurement scales spanning orders of magnitude, from kilometres to nanometres. At the reservoir (kilometres to meters) scale, satellite-based remote sensing, 4D seismic monitoring, tiltmeters, downhole sensors and tracers deployed within injection wells can offer precise data on CO_2 distribution. At the centimetre to nanometre scale, geochemical monitoring of produced fluids provides insights into CO_2 interactions with subsurface formations. The intermediate scale (meters to centimetre) is where conventional "well-based" measurements are conducted. These include the monitoring of CO_2 injection rates, well (annulus) pressures, casing pressure tests, and cased hole/production logging measurements. This enables a real-time assessment of CO_2 injection efficiency and potential leakage.

There have been documented instances where the abovementioned techniques have worked well in CO_2 containment monitoring. One example is the Equinor operated Sleipner Project in the North Sea where the operator utilised seismic surveys and downhole pressure measurements to demonstrate effective containment [4]. Yet, there are also documented instances where, despite extensive monitoring efforts, unexpected CO_2 leakage behaviour does occur. The In Salah project in Algeria, led by BP, Statoil, and Sonatrach, is one such example [5]. The latter underscores the importance of continual vigilance and timely adaptive management in CO_2 containment to mitigate risks effectively.

The above examples illustrate that it is sometimes not enough to rely solely on hardware based solutions like sensor measurements at the monitoring well. Rather, we postulate that subtle fluctuations in injection rates can act as a predicators for potential future containment breaches. By training a machine learning model to recognise these subtle fluctuations, potential containment breaches can be flagged prior to them occurring. If the model triggers in such events, the operator would simply need to shut the well in and investigate, for risk mitigation purposes.

The Significance and Complexity of Optimising CO_2 Injection Rates

Achieving optimised CO_2 injection involves maximizing the rate and volume of CO_2 while ensuring it remains in a supercritical state, thereby minimising phase transitions, vaporisation, and hydrate formation from the wellhead to the injection point. This necessitates meticulous consideration of three primary parameters: reservoir heterogeneity, pressure, and time.

Reservoir heterogeneity, encompassing permeability, porosity, and lithology, significantly influences injection rates. High-permeability formations facilitate rapid CO_2 flow, while geological features such as layering, faults, and fractures can both enhance CO_2 distribution and affect injection rates. Injecting CO_2 too rapidly can induce skin effects, diminishing overall field injectivity. Moreover, reservoir pressure, inversely correlated with the volume of CO_2 injected, must be carefully managed to prevent overfilling, which can lead to seismic activity and potential CO_2 containment breach.

In essence, comprehending the intricate interplay between reservoir capacity and injection parameters is imperative for ensuring the efficiency and safety of CO_2 sequestration endeavours. This understanding extends to recognising the temporal dynamics of CO_2 injectivity and its relationship with various influencing factors over time. Through the analysis of historical CO_2 injectivity data and its correlation with time-sensitive parameters, engineers can refine reservoir management strategies via modeling and scenario analysis. This approach allows for informed decision-making regarding CO_2 storage and utilisation projects, ultimately advancing the efficacy and sustainability of carbon capture and storage initiatives.

Literature Review

Various authors have tried numerous methods to forecast based on historical data. Work by De Gooijer and Hyndman [6], for instance, reviewed a series of time-series forecast models over a 25-year period, from 1985 to 2005. Their review highlighted various models being developed and applied in a myriad of scenarios related to finance, statistics and manufacturing, and included methods such as (a) exponential smoothing [7, 8], (b) Autoregressive Integrated Moving Average (ARIMA) [9], (c) seasonal models [10], (d) state space and structural models and the Kalman filter [11], (e) nonlinear models [12], (f) long-range dependence models, including the family of Autoregressive Fractionally Integrated Moving Average (ARFIMA) models [13], (g) Autoregressive Conditional Heteroskedasticity/Generalized Autoregressive Conditional Heteroskedasticity (ARCH/GARCH) models [14], and (h) count data forecasting [15].

Within reservoir engineering, the extrapolation of hydrocarbon and water recovery rates from geological formations into the future can be viewed as a type of time-series forecasting. Empirical solutions developed by Arps [16], referred to as decline curve analysis (DCA) technique is one of the earliest methods to address this problem. The method is based on a curve-fit principle, where one would attempt to fit either exponential, hyperbolic or harmonic curve to historical flow production rate as a function of time. Equation 1 shows the general form of the equation, while Equation 2 and Equation 3 are more specialised forms of the equation:

General Form (Hyperbolic Decline)

$$q(t) = \frac{q_i}{(1 + bD_i t)^{1/b}} \qquad \text{Equation 1}$$

Exponential Decline

$$q(t) = q_i\, e^{-dt} \qquad \text{Equation 2}$$

Harmonic Decline

$$q(t) = \frac{q_i}{(1 + bD_i t)} \qquad \text{Equation 3}$$

where q_t is the flow rate at time t (bbls/day), q_i is the initial flow rate (bbls/day), t is time (day), D_i is the initial decline rate (%), and b is the degree of curvature of the line (Arps' decline-curve exponent). A hyperbolic curve would have 0 < b < 1 and a harmonic curve would have b = 1. The fitted curve is then used to predict future production rates and cumulative production [17]. This method was originally designed to work with high porosity-permeability reservoirs and tends to overestimate hydrocarbon recovery from unconventional (low permeability) reservoirs. Thus, various authors have tried to expand on this work [18, 19, 20, 21], and are mostly variations of the initial DCA method developed by Arps. For an effective DCA forecast, domain and field knowledge are key, but inherently the process is one of trial and error, and thus it is not uncommon for DCA results to have 'low-best-high' estimates.

With the advent of big data, fast computing and cheap memory, applying a machine learning (ML) and artificial intelligence (AI) solution for time-series forecasting seems a natural evolution. ML solutions were first introduced to the petroleum industry in the early 2000s. Applications of ML and AI include addressing prediction of reservoir parameters [22], history matching, of oil, gas and water production forecasting (flow rate prediction), pattern recognition in well logs and well tests analysis, production enhancement and prediction of failures, among others [23, 24, 25].

ML algorithms have been used to predict carbon emissions [23], leakage [24], CO_2 absorption and adsorption [25], property prediction and process simulation [26], simulation of transportation, and geological behaviours as it relates to uncertainty analysis, sequestration, utilisation and EOR processes [26, 27, 28]. In the field of CCUS and well performance, work by Iskander et al [29] employs Long Short-Term Memory (LSTM) networks to forecast oil, water and CO_2 production at future infill well locations, for both single phase and 3-phase fluid models. Data were in the form of a synthetic PUNQ-S3 reservoir model, combined with real-world observations from 8 production wells, which recorded daily production volumes over a decade from 2004-2014 [29]. Injection data from CO_2 wells was not a direct input in the deep learning model, although it did play an indirect role in the oil and gas production data being recorded, as it swept the residual hydrocarbons and therefore resulted in an uplift in production rates.

We aim to develop on the work of Iskander and others by utilising ML and AI methods, and in particular LSTM, but focusing on the prediction of CCUS injection well performance, using the open-source information from the IBDP (Illinois Basin - Decatur Project) [3]. We will demonstrate how our developed LSTM model shows a correlation between the change in injection rate to the behaviour of other dynamic parameters [29].

One of the objectives of the model is to detect anomalies and alert operators to closely inspect the wells for potential leaks. While still adhering to local jurisdictional requirements of well annulus pressure monitoring, periodic pressure tests and cased hole logging, a ML model can be an additional method utilised to detect unexpected carbon leaks. We also view the model as another means for engineers to perform scenario based de-risking of exploration plays, via modelling variations in well and storage parameters to validate CO_2 containment. The model will also aid in the understanding of the injection process and potentially can be used to "right size" injection rates, well operations and optimise costs.

Scope and Methods

This paper aims to use time series injection information and monitoring data on a carbon sequestration well to predict carbon sequestration well injection rates deltas (Δ or inj_diff) which is the difference in the injection rate (IR) at time t and time (t-1) i.e.

$$\Delta = IR_t - IR_{t-1} \qquad \text{Equation 4}$$

Our primary source of data is from the Illinois Basin - Decatur Project, a CO_2 pilot project meant to demonstrate the capacity, injectivity, and containment of carbon storage in the Mount Simon Sandstone, the main carbon storage resource in the Illinois Basin and the Midwest Region (Figure 1(L)). The source of the injected CO_2 is from ethanol production at the Archer Daniels Midland company's plant. The CO_2 is compressed, dehydrated and injected into the Mt. Simon Sandstone, which is primarily a saline aquifer approximately ~7,000 ft deep. Injection began in 2009 and continued for a 3-year period (Nov-2011 to Nov-2014). Cumulatively, ~999,215 tonnes of supercritical CO_2 have been injected and geologically stored. A pair of injection and verification wells, ~1007ft apart, were drilled into the formation (Figure 1(R)). The wells were equipped with downhole sensors to monitor pressure and temperature at various depths of interest.

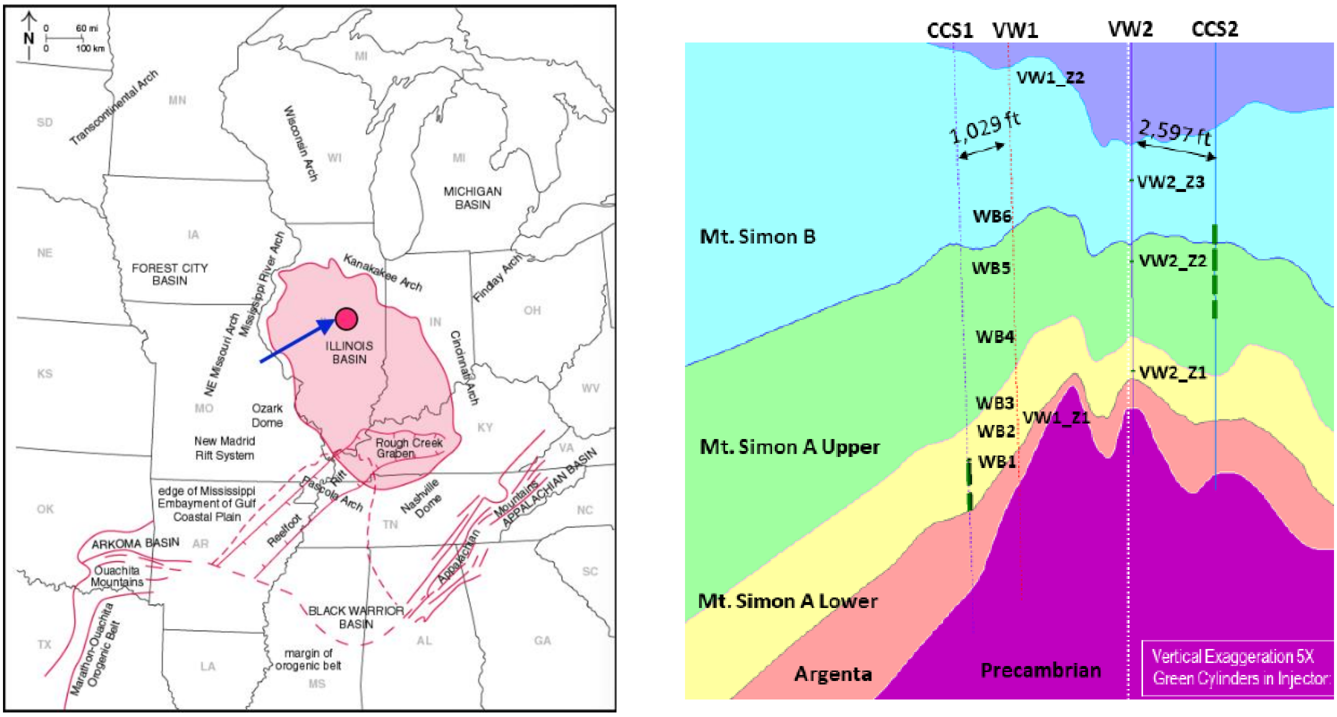


Figure 1: (L) Location map of the Illinois Basin – Decatur Project (IBDP). (R) Schematic illustration of the formation layers, location of perforation intervals in the CCS1 injector well (green cylinders) and the location of the verification well (VW1). Image taken from [3]

Datasets

During this three-year period, a substantial amount of data was collected from both an injection and monitoring well, 1007 ft apart. The injection well was drilled to a total depth (TD) of ~7238 ft, and was drilled with a 26” bit to 355 ft, and cased with a 20” casing to surface. A 17 ½” hole size then followed to a TD of 5339 ft, and an intermediate casing string 13 3/8” in diameter was set. The reservoir section was drilled in a 12 ½” hole size to ~ 7056 ft and completed with a 9 5/8” production casing and 4 ½” tubing. The perforations were made at the base (i.e. above the Precambrian) Mt. Simon Sandstone, which was a relatively thick reservoir of ~1620 ft. A total of 3 geophones were set at 4925 ft, 5743 ft and 6137 ft along with a pressure / temperature gauge mandrel at 6325 ft. The monitor well was drilled to a total TD of 7272 ft; it had a surface casing (13 3/8” to 377 ft, followed by intermediate casing of 9 5/8” to 5322 ft and 5 ½” casing across the Mt. St Simon Sandstone, which contained a 3 component geophone array) [3].

A. <u>Data Collection and Preparation</u>

A total of 34 parameters were measured from the injection and verification well. The parameters measured comprised of both surface and downhole measurements which were acquired at five second intervals over three full years. The sheer volume of data required that the time scale be downscaled to hourly intervals, taking the parameter average over the hour. 27,665 hours of data (training data) was used to build a suitable model. 67% of the “training” data set was used to train the model. The remaining 33% was used as a “validation” dataset. The model built off this data was finally used to predict 201 hours of Δ into the future (“hold out” data). Given in Table 1 is the descriptive statistics of the provided data; we refer readers to the nomenclature table for the definition of the variables. We note that there are a series of “null values” (including negative null values) and non-numeric numbers, missing rows, time gaps and note that for some of the input data measurements, there are significant outliers.

Table 1: Data Statistics

Measurement	Non-Zero Value	Mean Value	Standard Deviation	Minimum Value	25th Percentile	Median Value	75th Percentile	Maximum Value
Avg_PLT_CO2VentRate_TPH	27398.0	2.1	133.2	0.0	0.0	0.1	0.2	18333.2
Avg_CCS1_WHCO2InjPs_psi	27270.0	1239.9	817.7	0.0	1235.5	1338.9	1361.0	39032.4
Avg_CCS1_WHCO2InjTp_F	27398.0	89.8	48.3	0.0	93.0	96.3	96.9	2879.4
Avg_CCS1_ANPs_psi	27304.0	560.9	445.9	0.0	523.5	564.9	604.8	24105.6
Avg_CCS1_DH6325Ps_psi	27398.0	3244.2	173.5	0.0	3233.0	3286.1	3324.7	3515.9
Avg_CCS1_DH6325Tp_F	27398.0	127.7	7.2	0.0	127.2	130.1	131.1	135.7
Avg_VW1_WBTbgPs_psi	26127.0	1801.8	999.4	0.0	2173.5	2322.4	2379.8	4954.7
Avg_VW1_WBTbgTp_F	26061.0	80.8	44.3	0.0	103.4	104.2	105.0	120.1
Avg_VW1_ANPs_psi	23487.0	525.0	3988.7	0.0	0.5	4.7	16.9	31993.5
Avg_VW1_Z11D4917Ps_psi	26688.0	1597.5	873.3	0.0	2070.3	2073.4	2074.1	2378.0
Avg_VW1_Z11D4917Tp_F	26709.0	81.7	44.2	0.0	103.7	105.2	106.5	108.6
Avg_VW1_Z10D5001Ps_psi	26688.0	1627.9	889.9	0.0	2106.9	2112.4	2116.6	2420.6
Avg_VW1_Z10D5001Tp_F	26709.0	81.2	44.0	0.0	101.8	104.7	105.0	110.9
Avg_VW1_Z09D5653Ps_psi	26688.0	1961.1	1071.9	0.0	2534.0	2547.5	2551.1	2785.4
Avg_VW1_Z09D5653Tp_F	26709.0	87.4	47.3	0.0	111.5	112.8	113.5	114.9
Avg_VW1_Z08D5840Ps_psi	26189.0	1604.8	1289.3	0.0	0.0	2627.3	2637.4	4446.2
Avg_VW1_Z08D5840Tp_F	25878.0	69.0	56.4	0.0	0.0	114.0	115.0	353.2
Avg_VW1_Z07D6416Ps_psi	25985.0	2199.2	1273.0	0.0	0.0	2911.6	2925.3	3195.0
Avg_VW1_Z07D6416Tp_F	25985.0	88.8	50.8	0.0	116.5	116.9	118.6	145.1
Avg_VW1_Z06D6632Ps_psi	25500.0	2315.6	1308.6	0.0	3012.2	3026.1	3031.3	3380.4
Avg_VW1_Z06D6632Tp_F	25500.0	90.9	50.8	0.0	116.6	118.6	119.4	124.3
Avg_VW1_Z05D6720Ps_psi	23955.0	2106.0	1447.2	0.0	0.0	3069.6	3073.6	3365.9
Avg_VW1_Z05D6720Tp_F	23955.0	82.3	55.0	0.0	0.0	118.5	119.4	122.1
Avg_VW1_Z04D6837Ps_psi	26600.0	2347.5	1369.0	0.0	0.0	3148.0	3153.5	3331.9
Avg_VW1_Z04D6837Tp_F	26600.0	91.0	51.6	0.0	118.8	119.5	119.9	125.8
Avg_VW1_Z03D6945Ps_psi	24361.0	2350.9	1495.7	0.0	0.0	3299.9	3320.6	3457.9

Avg_VW1_Z03D6945Tp_F	25932.0	182.3	368.5	0.0	0.0	121.3	122.8	1602.9
Avg_VW1_Z02D6982Ps_psi	26423.0	2456.6	1459.1	0.0	0.0	3316.2	3332.0	3499.6
Avg_VW1_Z02D6982Tp_F	26423.0	91.3	52.7	0.0	32.0	121.3	122.0	124.3
Avg_VW1_Z01D7061Ps_psi	25307.0	2300.2	1521.4	0.0	0.0	3318.2	3327.3	3445.1
Avg_VW1_Z01D7061Tp_F	25108.0	85.9	55.4	0.0	0.0	121.4	122.6	133.9
Avg_VW1_Z0910D5482Ps_psi	26709.0	1855.6	1017.6	0.0	2353.3	2374.9	2416.1	2758.3
Avg_VW1_Z0910D5482Tp_F	26709.0	86.3	46.7	0.0	110.5	111.5	112.0	113.7
inj_diff	27397.0	0.0	82.7	-11021.1	-0.1	0.0	0.1	7033.5

B. Cleaning Data

We reviewed the attributes for the data, and were especially concerned about discontinues, non-numerical data or data that were clearly outliers (e.g. ~25,000 psi WHP at injection well or 0 psi downhole gauge pressure). We utilised 4 methods to clean the data, in order of operation (i) we firstly performed a computational fill of all the missing and null values with a “forward fill’ operation, with the last valid observation being propagated forward. We do this on the assumption that missing values retain the properties of the previous cell i.e. there has been no change in the data between time *t* and time (*t-1*), (ii) a Z-score method where

$$Z = \frac{x_i - \tilde{x}}{MAD} \quad \text{Equation 5}$$

x_i is a single data value, $\tilde{x}$ is the median of the data set and MAD is the median absolute deviation of the dataset, (iii) removing values of formation pressure that we know to be technically invalid and (iv) a final visual check of the data, removing outliers that we view as being deleterious to the interpretation. Shown in Figure 2 is an example of the impact that data cleaning has on the data quality. We see that our process has removed spikiness in the data and smoothed out some of the small-scale perturbations, resulting in a more manageable dynamic range.

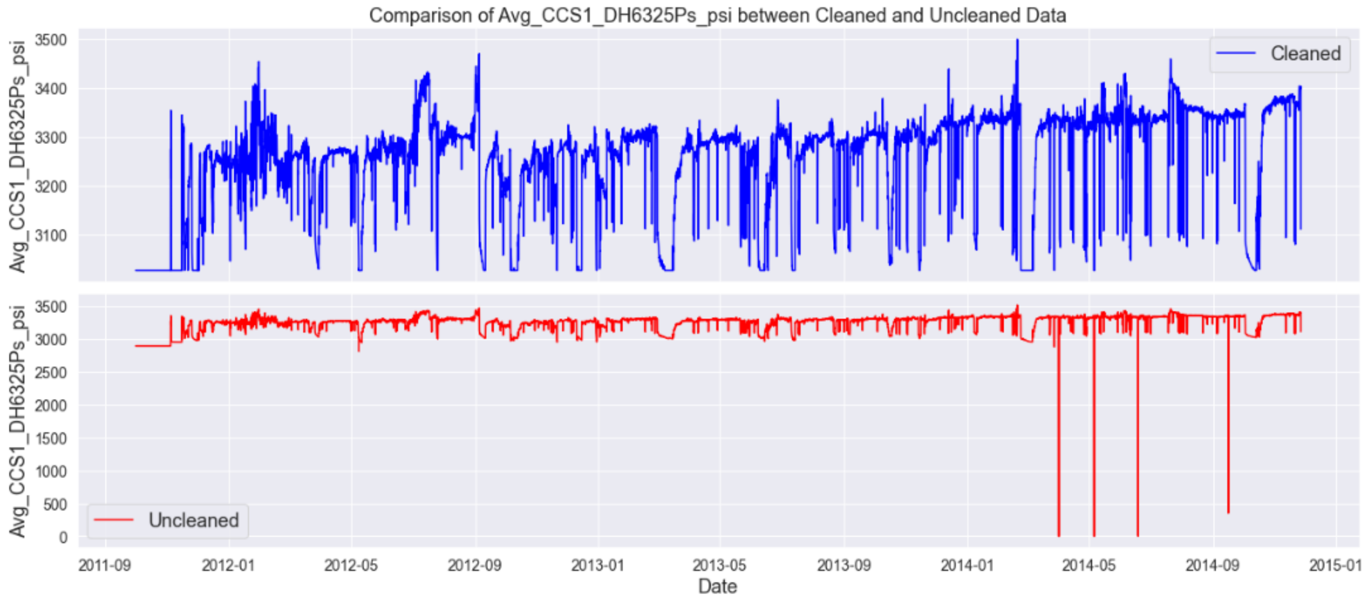


Figure 2: An example of the measurement before (lower image) and after (upper image) data cleaning.

C. <u>Machine Leaning Model Selection - Long Short-Term Memory (LSTM) vs. Autoregressive Integrated Moving Average (ARIMA)</u>

In the choice of ML model to apply, we had to decide between a statistical approach based on ARIMA, or alternatively, the use of a non-linear algorithm such as neural networks (NN). Many authors have investigated comparing such methods and in various fields. What we noted from our review of the work was there was a general agreement that approaches like ARIMA would not only require less inputs, but would be less of a “black-box”, which NNs are known to be [30, 31, 32].

ARIMA has been applied by previous authors to forecast oil production data [33]. The “autoregressive” piece of ARIMA deals with finding a correlation between a specific value and a prior/lagged value, essentially seeing if a variable has any correlation to its past values. The “integrated” piece deals with making data stationary, essentially ensuring that properties of the data (such as mean and variance), are constant over time. The “moving average” piece of the model finds the dependency between a specific value, and the error from a moving average model applied to previous values. ARIMA models are therefore useful in forecasting time series data and are especially useful when trying to predict time series data that is non-stationary. While Ning et al observed that ARIMA was robust in predicting rates of oil production across wells, our review of ARIMA models being produced with high frequency data, where accuracy on an hourly basis was important, found that the error rate compounds significantly when the forecasting horizon is extended beyond a day [34].

LSTM is a type of recurrent NN which uses useful patterns from sequential data to provide accurate forecasts [23]. It learns from previous outputs to provide better results the following time. A typical LSTM has 3 layers (i) an input gate which assigns weights based on the significance of different variables, (ii) a forget gate to retain only useful information, and (iii) an output gate which manages the information flow. LSTM holds a memory cell (known as a cell state) which retains captured information over longer time periods and preserves useful constituents using its input and forget gates, hence avoiding the vanishing gradient issue associated with traditional NNs. LSTMs are particularly useful for non-linear problems where there does not appear to be strict mathematical relationships between variables. Unlike recurrent NNs, LSTMs can account for long-term temporal effects without encountering optimisation hurdles like vanishing gradients [35]. In our review of LSTM vs ARIMA models, we have found a common consensus in various fields that LSTM performed better, with reduced error rates but with significantly increased processing time [32, 31].

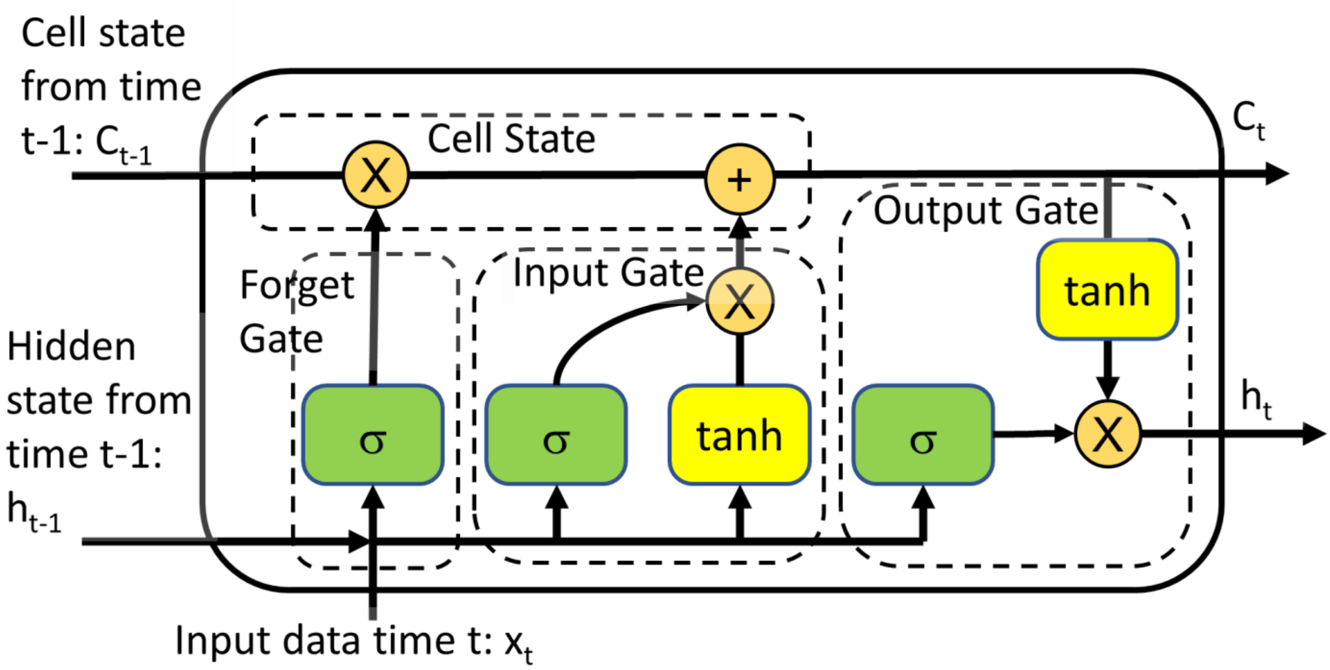


Figure 3: Schematic of LSTM network

We settled on the choice of LSTM because we realised that the data we were analysing was likely to contain non-seasonal, high frequency information, where accuracy was going to be important [36]. Additionally, the were numerous variables provided which we did not know the relative importance of in prediction without a working model.

D. Model Performance and Hyperparameter Optimization

We access the model performance using a host of measures, from training and validation loss to mean absolute error (MAE - Equation 6), mean squared error (MSE - Equation 7), root mean squared error (RMSE - Equation 8) and the coefficient of determination (R^2 - Equation 9). The training and validation loss functions serve to determine how well the model is performing and to prevent overfitting. During training, the model learns by iteratively adjusting its parameters to minimize a defined loss function. The training loss measures the discrepancy between the model's predictions and the actual target values on the training data. The goal is the minimization of this loss, as it indicates how well the model is fitting the training data. The validation loss is the other component of this and is computed by evaluating the model's performance on a separate validation dataset, not used for training. It serves as an estimate of how well the model generalizes to unseen data.

MAE: $$\frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \quad \text{Equation 6}$$

MSE: $$\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \quad \text{Equation 7}$$

RMSE: $$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad \text{Equation 8}$$

R^2: $$1 - \frac{\sum(y_i - x_i)^2}{\sum(x_i - \bar{x})^2} \quad \text{Equation 9}$$

Equation 6 to Equation 9 show the other measurement metrics, with y_i as the predicted value, x_i as the true value, $\bar{x}$ as the mean of x_i and n as the total number of data points. MAE measures the average absolute difference between the predicted and actual values and provides an absolute measure of the model's performance. MSE measures the average squared difference between the predicted and actual values and amplifies larger errors due to the squaring operation. RMSE is the square root of MSE and provides a measure of the average magnitude of errors. It is useful for interpreting errors in the same units as the target variable. R^2 measures the proportion of the variance in the target variable that is explained by the model. It ranges from 0 to 1, where 1 indicates a perfect fit and 0 indicates a poor fit.

While MAE, MSE, RMSE, and R^2 are evaluation metrics used to assess the model's performance after training, the (training and validation) loss functions are specific to the training process. These loss functions guide the model's learning by providing gradients for updating the model's parameters. However, the suitability of the model is ultimately guided by scores where the MAE, MSE and RMSE and low, while the R^2 is high.

The NN model is tuned by varying a series of “hyperparameters”. A hyperparameter is a characteristic of a model that is external to the model and whose value cannot be estimated from data. The hyperparameters that were optimized included the (i) learning rate, (ii) the epochs, (iii) the number of neurons, (iv) the magnitude of dropout, (v) batch size, (vi) the choice of optimiser and finally (vii) the choice of activation function. To account for idiosyncrasies in the data (noise, patterns, outliers, etc.), k-fold cross-validation was run to validate the stability of the model.

Results and Discussion

Data Preparation

We observed significant collinearity of > 0.8 across most of the data set. Most were paired couplet measurements of “Temperature” and “Pressure” at various gauge depths. Keeping both parameters adds no additional information to the predictive model and in fact may be detrimental, with potential overfitting. Therefore, a single element from each of the variable pairs is eliminated to allow for a more stable model. Exceptions were made if variables were found to be from different sources e.g. tubing and reservoir pressure at the observation well for instance. This is also in line with conventional reservoir engineering concepts where temperature and pressure are correlated.

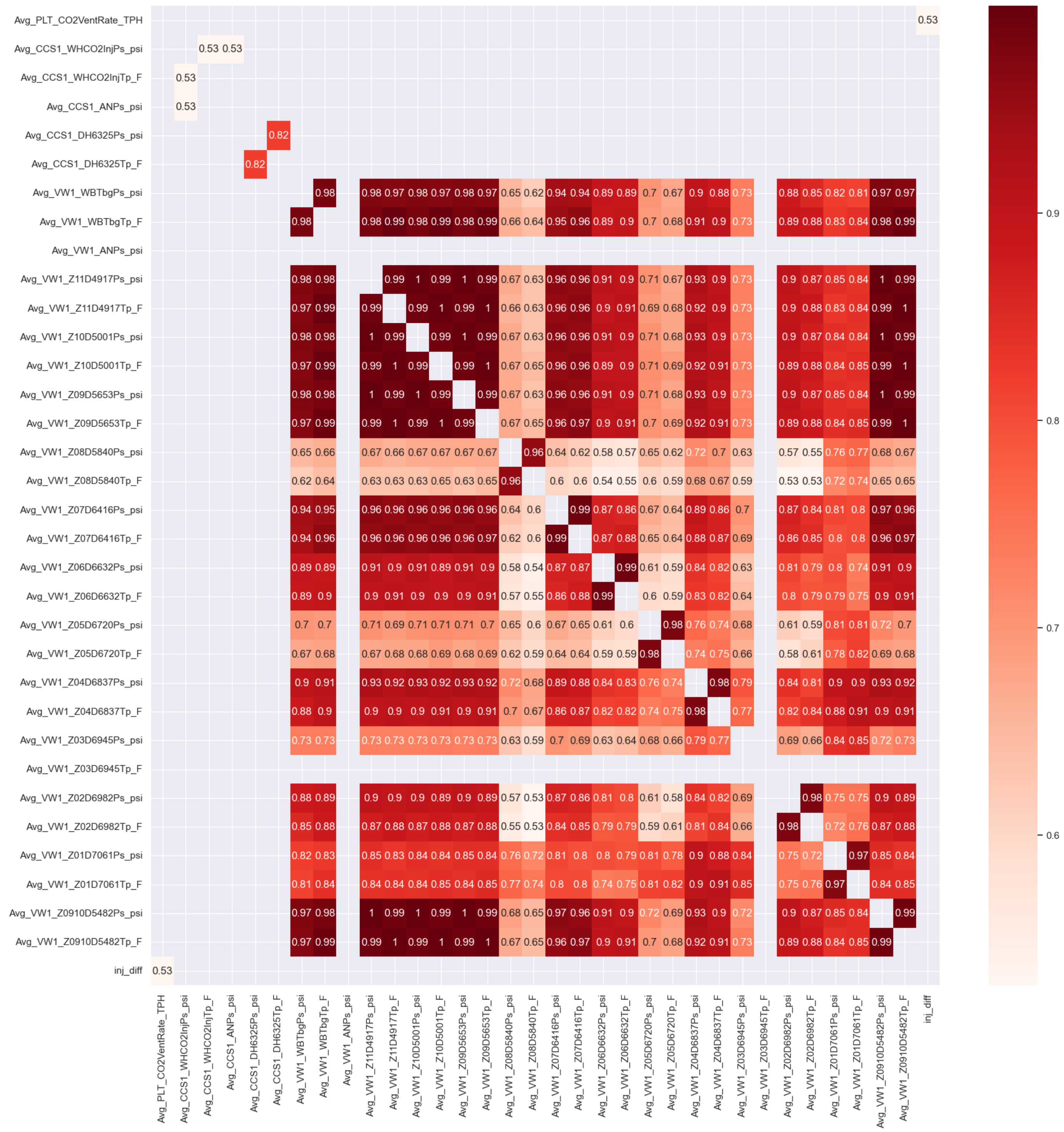


Figure 4: Correlation Matrix – Pairwise Correlation. It ranges from -1 to 1, -1 being a perfect negative correlation and +1 being a perfect positive correlation. The color scale visually depicts this: dark/warm show strong correlations

Excluding the target injection delta variable, eight variables were retained for the machine learning application and are summarised in Table 2 for the entire dataset. All data is numerical data types. The total data size is 27,665 values per column, for a total of 248,784 data points which was approximately ~26% of the original data base.

Table 2: Statistics of the cleaned dataset

Measurement	Non-Zero Value	Mean Value	Standard Deviation	Minimum Value	25th Percentile	Median Value	75th Percentile	Maximum Value
Avg_PLT_CO2VentRate_TPH	27,665	1.015	3.94	0	0	0.06	0.15	60
Avg_CCS1_WHCO2InjPs_psi	27,665	1253	191	701	1233	1339	1361	1882
Avg_CCS1_WHCO2InjTp_F	27,665	91	12	59	93	96	97	120
Avg_CCS1_ANPs_psi	27,665	554	102	149	523	565	605	977
Avg_CCS1_DH6325Ps_psi	27,665	3254	106	3006	3234	3286	3326	3516
Avg_CCS1_DH6325Tp_F	27,665	128	4.58	117	127	130	131	136
Avg_VW1_WBTbgPs_psi	27,665	2248	452	60	2233	2343	2421	4817
Avg_VW1_Z05D6720Ps_psi	27,665	3043	233	282	3061	3072	3075	3366
inj_diff	27,665	0.03	3.74	-38	-0.08	0	0.07	38

LSTM Model Architecture

We have employed a stacked LSTM architecture, with 2 layers, for this evaluation. In a stacked LSTM model, the output sequence of one LSTM layer serves as the input sequence for the next LSTM layer in the stack. This allows for a hierarchical representation of the input data, with each LSTM layer capturing different levels of abstraction or temporal dependencies. The second layer of the stacked model feeds the results to the output layer. We also use dropout to reduce the risk associated with overfitting. Finally, there is a dense layer which predicts the output, a single timestep at a time.

We tested the performance of the model by varying the hyperparameters given in Table 3. We utilised K-fold cross validation for hyper parameter tuning, ensuring that we kept the time series harmony. By this, what we mean is we split the time series sequence into samples but retained the sequence of information. With each split, a model is trained using (k-1) folds of the training data. The model is then validated against the remaining fold. A final model is scored on the held-out fold, with scores averaged across the splits. We used this to refine our hyperparameters, and finally took an average of values you see in Table 3.

Each hyperparameter serves a specific purpose and it is fundamentally an iterative process to tune these parameters such that the model outputs are optimised. We broadly define each hyperparameter here, sharing more details in Table 3. The same table also shows our final selected values based on an optimised MSE value.

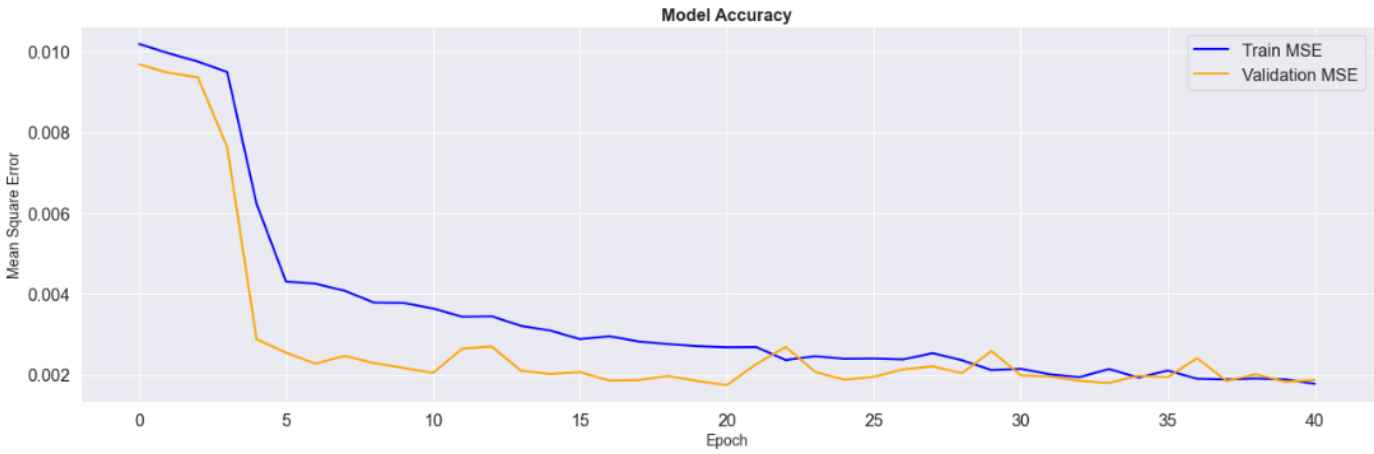
The learning rate refers to the model's degree of responsiveness to errors. Epochs refer to the number of iterations across the entire dataset, while neurons are the fundamental nodes/building blocks used to process inputs. Dropout refers to the proportion of randomly selected neurons which get deactivated (to prevent overfitting) and batch size addresses the quantity of inputs processed before updating the model. An optimiser algorithm is needed to minimize the loss function, by finding the optimal set of parameter values that lead to improved network performance. Finally, the activation function is a mathematical function which introduces non-linearity to the layer of neurons.

Table 3: Variation in Hyperparameter Values, Final Selected Values and Parameter descriptor

Measure	Minimum	Maximum	Final	Parameter Descriptor
Learning Rate (lr)	0.001	0.1	0.01	The rate at which the parameters (weights and biases) of the network are updated during the training process. It essentially controls how quickly or slowly the network learns from the gradients of the loss function.
Epochs	10	100	50	This parameter determines how many times the learning algorithm will iterate over the entire training dataset. Each iteration has the following steps (a) forward propagation, (b) loss computation, (c) backpropagation,

				and (d) update. These steps are repeated in the training dataset until all samples have been processed. This completes one epoch.
Neurons	10	50	20	Each neuron takes multiple inputs, performs a computation on those inputs, and produces an output. The computation typically involves applying a weighted sum of the inputs, followed by the application of an activation function.
Dropout	0.1	0.25	0.25	This parameter introduces noise or randomness into the network by temporarily removing a portion of the neurons from the calculation in each training iteration. By doing so, dropout prevents complex co-adaptations between neurons, reducing the reliance of the network on specific neurons and promoting the learning of more robust and generalized representations.
Batch Size	30	100	50	This parameter refers to the number of training examples that are processed together in a single forward and backward pass during training.
Optimiser	-	-	Adam	ADAM (Adaptive Moment Estimation) is an optimization algorithm used to update the weights of neural networks during the training process. It automatically adjusts the learning rate for each parameter based on the history of gradients. This was chosen as the default optimizer as it has the ability to converge quickly as well
Activation	-	-	tanh	The hyperbolic tangent function maps the input to a value between -1 and 1. It has an S-shaped curve like the sigmoid function but is symmetric around the origin. The formula for tanh is: $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

Figure 5 shows the MSE output of the training (train) and validation (val) sets for one of our K-folds. MSE is on the y-axis and epoch is on the x-axis. We observe the convergence between train and val, telling us that the model accuracy is improving per epoch. The point of convergence is arrived at by gradient descent and tells us the point of minimum information loss. In this example, we achieved convergence at around epoch = 30, with losses increasing beyond that.



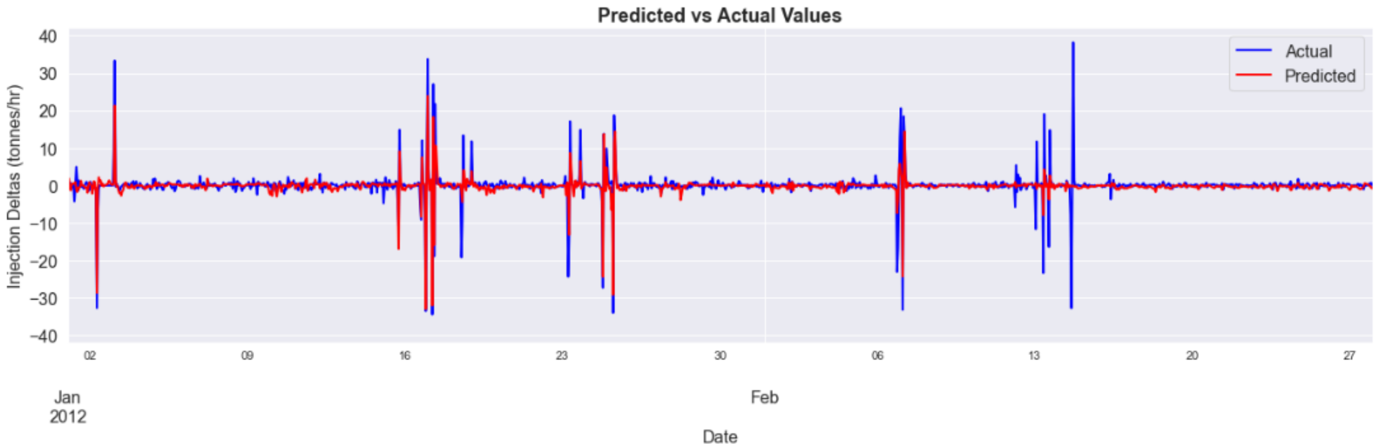
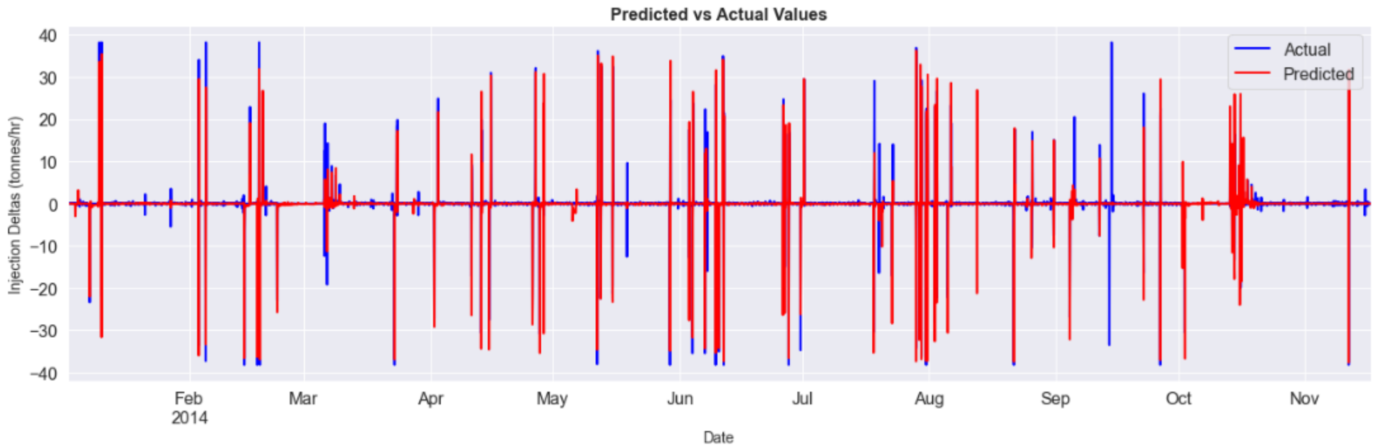


Figure 5: (Upper) MSE output of the training and validation set (Lower) Check file of a small subset of data; output from the K-fold set.

Prediction on Validation Data

We deployed our developed model on our validation data. Given in Figure 6 is the comparison between the predicted injection rate deltas versus the actual injection rate deltas in our validation set. The results demonstrate the model's capability to successfully identify and replicate actual anomalies, which provides evidence that the model is predictive in nature. Moreover, Figure 6 illustrates that the model can accurately capture both large scale high frequency signal, as well as smaller scale fluctuations in the injection deltas (admittedly, the subtle variations are harder to capture as these change at ranges of ± 1psi and can be described to be in the domain of "noise"), indicating the robustness of the LSTM model.

The fact that the model can capture both large and small-scale measures strengthen our view that the model is indeed reliable in handling the variety of conditions experienced in the field during CO_2 injection, and hints at its ability to effectively mimic the intricate patterns found within field injection rate data. The successful reproduction of significant anomalies as well as subtle variations highlights the model's potential to provide valuable insights and reliable predictions in this domain.



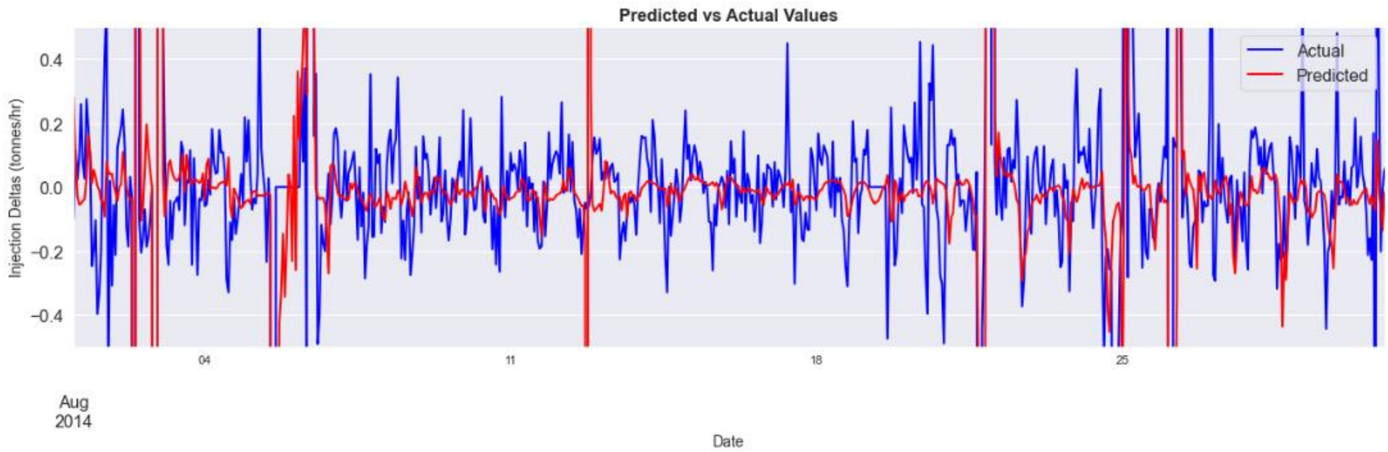


Figure 6: (Upper) Able to match anomalies in injection delta (Lower) Able to mimic the small variations in the injection delta.

Generalising the model

This LSTM model was built from (what is fundamentally) a single data set i.e. from a specific geological rock type, whose CO_2 flow behaviour is constrained by its own petrophysical and reservoir engineering properties. We think further generalisation of the model is necessary to truly confirm these findings. As we do not have data from other geological settings, we attempted generalisation through a series of sensitivity runs. We did this in 2 ways (a) selecting a single seed value but varying the input parameters fed into the model and (b) by randomising the seed value itself but keeping the input parameters constant.

(a) Single Seed, Variable Inputs

We used a single seed value (2250) but varied six of the selected as a test for model generalisation. Our first iteration (Run 1 in Table 4) is with a default hyperparameter setting, where the predicted injection delta is zero for all test timesteps; this yielded an RMSE value of 5.54 (Run 1 in Table 5).

Several adjustments were made to the inputs from that base case defined in run 1. These modifications included (a) scaling all columns within a range of -1 to 1 (runs 2 to 6), (b) replacing, as one of the input variables, the VW DH Z09 sensor with the VW DH Z05 sensor (runs 4 to 6), (c) incorporating well head pressure (WHP) sensor data (runs 2 to 4, run 6), (d) using temperature sensor data (runs 5 and 6), (e) increasing the Z-score band for the target column from 20 to 25 (runs 3 to 6), and (f) utilizing corrected values of zero for the VW DH sensor (runs 3 to 6).

By analysing the results of these runs and comparing them to the base and default settings, it is possible to determine the most optimal configuration that yields improved accuracy and reliability in predicting injection deltas. This series of sensitivity runs showed us that the model performs most optimally based on the configuration in run 6. It additionally tells us that the model is sensitive to scaling, and our Z-score tolerance bands.

Table 4: Inputs to test for the effect of randomness in the model

Varied Parameter	Run 1 (Base Case)	Run 2	Run 3	Run 4	Run 5	Run 6 (Final Model)
Scaling	N	Y (0,1)	Y (-1,1)	Y (-1,1)	Y (-1,1)	Y (-1,1)
VW DH Sensor	NA	Z01	Z05	Z05	Z01	Z05
Injection WHP Sensor	NA	Y	Y	N	Y	Y
Temp Sensor	NA	N	N	Y	Y	Y
Z-Score Tolerance	NA	25	25	25	25	25

Table 5: RMSE and R2 output values to determine if the model is accurately able to account for randomness

Parameter	Run 1 (Base Case)	Run 2	Run 3	Run 4	Run 5	Run 6 (Final Model)
Test RMSE	5.54	1.82	1.98	1.50	1.48	1.49
Val RMSE	NA	2.20	1.90	2.01	1.71	1.49
Val R2	NA	0.63	0.72	0.69	0.78	0.83

Randomness

NN themselves are not inherently stochastic, as they follow deterministic mathematical operations, and the inputs, weights, and biases are all fixed values during inference. However, the stochastic nature of the NN model becomes apparent when seed values are varied; different seed values result in different results.

Our next test for the generality of the model involved running various seed values (we utilised 10 different values) and determining if both high and low amplitude delta values could be predicted. Seven selected results are displayed in Table 6 while Figure 7 to show the range of comparison with respect to the first unseeded run.

We observe that while all runs can predict the anomalies, the signature of the minor differences varies between seed values (Table 6). We also observe that the RMSE and R2 values on the validation set all lie within a small range (±10% or up to 0.2 psi absolute) of the unseeded value (Figure 7). Thus, to account for randomness and to retain the unbiased nature of the model, an unseeded model is selected for deployment.

Table 6: RMSE and R2 value of sensitivity runs to test randomness of model

Variables	Run 1 (Base Case)	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7
Seed Value (SV)	Unseeded	2250	42	2023	1	111	88
Val RMSE	1.79	1.55	1.69	1.69	1.64	1.87	1.70
Val R2	0.83	0.82	0.78	0.78	0.79	0.73	0.78

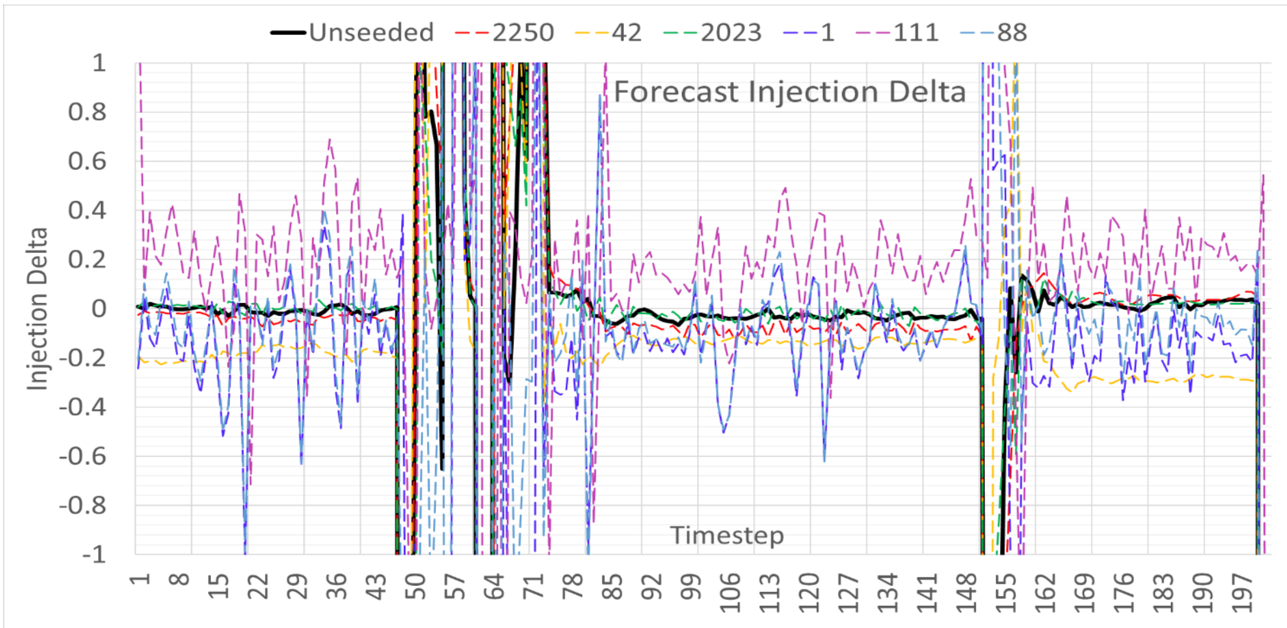


Figure 7: Injection Delta forecasts of sensitivity run to test randomness of model – all results show small perturbations around the unseeded value

Evaluation against the "Hold-out" Data

We test the predictive capability of the model by passing downhole sensor measurements never seen by the model (our "hold out" data set), to determine if the model can detect injection rate anomalies.

Figure 8 shows the results of this test, where our model has successfully predicated the presence of four anomalies in the injection rates. When we plot this prediction against what the actual injection rates were (our “ground truth” data), we observe a near perfect overlap in results.

Error! Reference source not found.

We observe that for the negative injection deltas, there are corresponding decreases in injection pressure implying a decreased CO_2 injection rate. The prediction data also shows corresponding increase in injection pressure during positive injection deltas, implying an increased injection rate. Corresponding changes can also be seen on the other inputs such as temperature and CO_2 vent rate.

The fact that our model can predict these anomalies using measured sensor data is encouraging; as an operator who is interpreting this result, it would be prudent to firstly ask if these injection deltas are expected. If they are not, then it behoves the operator to investigate/ monitor the well to determine what sort of remedial action should be taken.

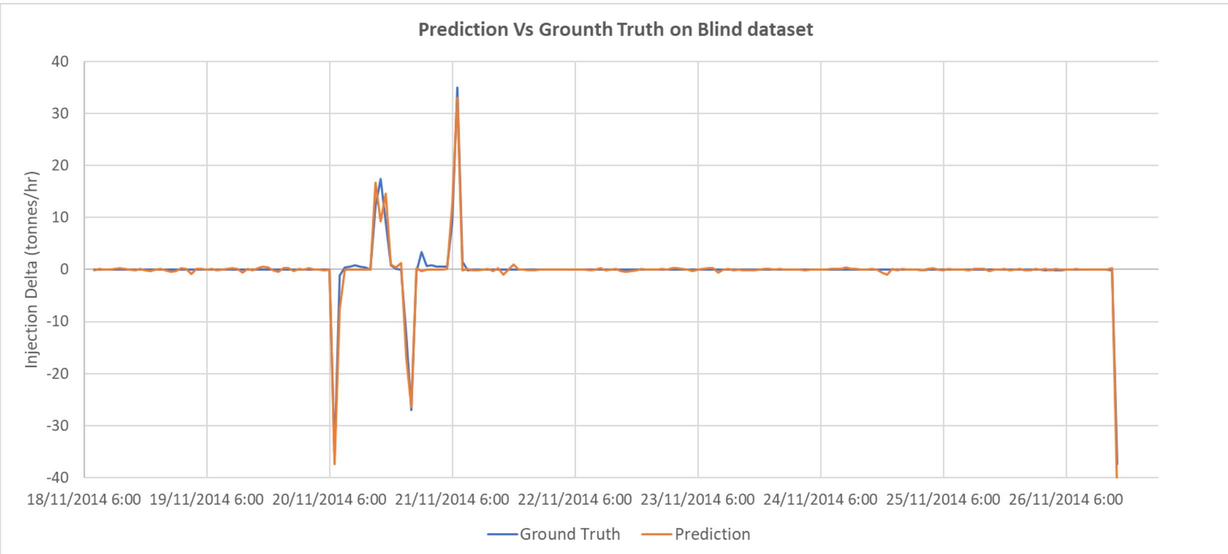


Figure 8: Input (blue line) and prediction (red line) on blind “hold out” dataset

Discussion & Recommendations

We think there are several ways to further enhance the model's performance. First, incorporating the response of the operator when an anomaly is marked as safe reduces the likelihood of flagging similar anomalies in the future. This feedback loop mechanism can help refine the model's predictive accuracy and ensure more reliable results over time.

Secondly, exploring alternative methods for outlier removal, and implementing advanced techniques to identify and handle outliers effectively will improve the model's ability to identify genuine anomalies, while minimizing false positives.

Thirdly, the workflow of the model can be improved to reduce runtime. This optimization involves running multiple sets of model ensembles, and aggregating their outputs to obtain a more "generalised" model. Generalising the model can further enhance performance and provide more reliability when it comes to anomaly detection.

Lastly, we also think the results of the model need integration with other monitoring technology; 4D seismic monitoring, tiltmeters, downhole sensors, tracers deployed and geochemical monitoring are just some examples of other data sets that should be incorporated.

Conclusion

The IBDP project involved injection of ~1000 tonnes/day of CO_2 into a single well, for a three year, resulting in ~995, 215 cumulative tonnes of CO_2 being injected. In view of the growing importance of CCUS in achieving climate targets, we believe the wealth of open-source time-series data from this project can be applied to derisk CCUS monitoring.

In this work, we demonstrated how an LSTM based machine learning model has been developed and implemented to predict injection deltas of active CO_2 injection. We demonstrate that our predicted models do well based on RMSE and R2 scores against both the training and validation data sets. Our model was able to predict both large and small anomalies, and we demonstrated that the model is sufficiently generalised for this single input data source.

The model can detect anomalies which operators can use when determining which wells to inspect for potential leaks, especially in scenarios where multiple wells are used for injection. By passing the measured data through the model, one can determine at which well location downhole losses were observed during the injection process. The model can also help engineers to perform computational based de-risking of geological formations, by understanding how changing certain storage parameters impacts CO_2 containment. The model will also aid in the understanding of the injection process and optimising well operations and costs, reducing the reliance on periodic (or ad-hoc depending on operator budget) tests like well annulus pressures, casing tests, and use of cased hole reservoir saturation tools.

We also recommended a series of improvements and model enhancements in this paper which would increase the machine learning model's predictive ability, potentially providing operators with timely alerts for potential leaks while optimizing operational efficiency and cost-effectiveness.

<u>Nomenclature</u>

GHG	greenhouse gas
CO_2	carbon dioxide
CH_4	methane
N_2O	nitrous oxide
EPA	Environmental Protection Agency
CCUS	Carbon Capture Utilisation and Storage
EOR	Enhanced Oil Recovery
Δ	injection rates deltas
IR	injection rate
ML	machine learning
ARIMA	Autoregressive Integrated Moving Average

ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARCH/GARCH	Autoregressive Conditional Heteroskedasticity/ Generalized Autoregressive Conditional Heteroskedasticity
DCA	decline curve analysis
q_i	initial rate (bbls/day)
D_i	initial decline rate (units)
b	degree of curvature of the line
AI	artificial intelligence
LSTM	Long Short-Term Memory
IBDP	Illinois Basin - Decatur Project
TD	total depth
MAD	median absolute deviation
NN	neural networks
MAE	mean absolute error
MSE	mean squared error
RMSE	root mean squared error
R^2	coefficient of determination
lr	Learning Rate
ADAM	Adaptive Moment Estimation
Z score	a statistical measurement describing a value to the mean of a group of values
CCS1_ANPs_psig	CCS1 annulus pressure in psi
CCS1_DHPs_psig	CCS1 downhole pressure in psi
CCS1_DHTp_F	CCS1 downhole temperature in Deg F
CCS1_WHCO2InjPs_psi	CCS1 wellhead pressure in psi
CCS1_WHCO2InjTp_F	CCS1 wellhead temperature in Deg F
PLT_CO2InjRate_TPH	CO2 injection rate in tonnes per hour

PLT_CO2VentRate_TPH	CO2 vent rate in tonnes per hour
VW1_ANPs_psig	Validation well (VW1) annulus pressure in psi
VW1_PTbgPs_psig	VW1 tubing pressure in psi
VW1_PTbgTp_F	VW1 tubing temperature in Deg F
VW1_Z01D7061Ps_psi	VW1 Zone01 pressure (7061 ft) in psi
VW1_Z01D7061Tp_F	VW1 Zone01 temperature (7061 ft) in Deg F
VW1_Z02D6982Ps_psi	VW1 Zone02 pressure (6982 ft) in psi
VW1_Z02D6982Tp_F	VW1 Zone02 temperature (6982 ft) in Deg F
VW1_Z03D6945Ps_psi	VW1 Zone03 pressure (6945 ft) in psi
VW1_Z03D6945Tp_F	VW1 Zone03 temperature (6945 ft) in Deg F
VW1_Z04D6837Ps_psi	VW1 Zone04 pressure (6837 ft) in psi
VW1_Z04D6837Tp_F	VW1 Zone04 temperature (6837 ft) in Deg F
VW1_Z05D6720Ps_psi	VW1 Zone05 pressure (6720 ft) in psi
VW1_Z05D6720Tp_F	VW1 Zone05 temperature (6720 ft) in Deg F
VW1_Z06D6632Ps_psi	VW1 Zone06 pressure (6632 ft) in psi
VW1_Z06D6632Tp_F	VW1 Zone06 temperature (6632 ft) in Deg F
VW1_Z07D6416Ps_psi	VW1 Zone07 pressure (6416 ft) in psi
VW1_Z07D6416Tp_F	VW1 Zone07 temperature (6416 ft) in Deg F
VW1_Z08D5840Ps_psi	VW1 Zone08 pressure (5840 ft) in psi
VW1_Z08D5840Tp_F	VW1 Zone08 temperature (5840 ft) in Deg F
VW1_Z0910D5482Ps_psi	VW1 Zone0910 pressure (5482 ft) in psi
VW1_Z0910D5482Tp_F	VW1 Zone0910 temperature (5482 ft) in Deg F
VW1_Z09D5653Ps_psi	VW1 Zone09 pressure (5653 ft) in psi
VW1_Z09D5653Tp_F	VW1 Zone09 temperature (5653 ft) in Deg F
VW1_Z10D5001Ps_psi	VW1 Zone10 pressure (5001 ft) in psi
VW1_Z10D5001Tp_F	VW1 Zone10 temperature (5001 ft) in Deg F

VW1_Z11D4917Ps_psi	VW1 Zone11 pressure (4917 ft) in psi
VW1_Z11D4917Tp_F	VW1 Zone11 temperature (4917 ft) in Deg F
inj_diff	difference in the injection rate (IR) at time t and time (t-1) in psi

Acknowledgements

The authors wish to acknowledge Ryan Lazaroo for peer review of this work.

Reference

[1] T. Nakazawa , “Current understanding of the global cycling of carbon dioxide, methane, and nitrous oxide.,” *Proceedings of the Japn Academy, Series B Physical and Biological Sciences,* vol. 96, no. 9, pp. 394-419, 2020.

[2] Z. Liu, Z. Deng, S. Davis and P. Ciais, “Monitoring global carbon emissions in 2022,” *Nature reviews earth and enviroment,* vol. 4, pp. 205-206, 2023.

[3] R. A. Bauer, R. E. Will, S. Greenberg and S. G. Whittaker, “Illinois Basin – Decatur project.,” in *Geophysics and Geosequestration*, Cambridge University Press, 2019, pp. 339-370.

[4] T. A. Torp and J. Gale, “Demonstrating storage of CO2 in geological reservoirs: The Sleipner and SACS projects.,” *Energy* , vol. 29.9, no. 10, pp. 1361-1369, 2004.

[5] P. S. Ringrose, A. S. Mathieson, I. W. Wright, F. Selama, O. Hansen, R. Bissell, N. Saoula and J. Midgley, “The In Salah CO2 Storage Project: Lessons Learned and Knowledge Transfer,” *Energy Procedia,* vol. 37, pp. 6226-6236, 2013.

[6] J. G. D. Gooijer and R. J. Hyndman, “25 years of time series forecasting,” *International Journal of Forecasting,* vol. 22, no. 3, pp. 443-473, 2006.

[7] E. S. Gardner, “Exponential smoothing: The state of the art,” *Journal of Forecasting,* vol. 4, no. 1, pp. 1-28, 1985.

[8] R. D. Snyder, “Recursive Estimation of Dynamic Linear Models,” *Journal of the Royal Statistical Society. Series B (Methodological),* vol. 47, no. 2, p. 272–276, 1985.

[9] R. H. Scumway and D. S. Stoffer, Time Series Regression and ARIMA Models, New York: Springer, 2000.

[10] G. Huyot, K. Chiu, J. Higginson and N. Gait, “Analysis of Revisions in the Seasonal Adjustment of Data Using X-11-Arima Model-Based filters,” *International Journal of Forecasting,* vol. 2, no. 2, pp. 217-229, 1986.

[11] S. H. Babbs and K. B. Nowman, “Kalman filtering of generalized Vasicek term structure models,” *Journal of financial and quantitative analysis,* vol. 34, no. 1, pp. 115-130, 1999.

[12] M. P. Clements, P. H. Franses and N. R. Swanson, “Forecasting economic and financial time-series with non-linear models,” *International journal of forecasting,* vol. 20, no. 2, pp. 169-183, 2004.

[13] B. K. Ray, “Long-range forecasting of IBM product revenues using a seasonal fractionally differenced ARMA model,” *International Journal of Forecasting,* vol. 9, no. 2, pp. 255-269, 1993.

[14] S. J. Taylor, “Forecasting the volatility of currency exchange rates,” *International Journal of Forecasting,* vol. 3, no. 1, pp. 159-170, 1987.

[15] T. R. Willemain, C. N. Smart, J. H. Shockor and P. A. DeSautels, “Forecasting intermittent demand in manufacturing: a comparative evaluation of Croston's method,” *International Journal of Forecasting,* vol. 10, no. 4, pp. 529-538, 1994.

[16] J. J. Arps, “Analysis of Decline Curves,” *Transactions of the AIME,* Vols. SPE-945228-G, no. 160, p. 228–247, 1945.

[17] M. J. Fetkovich, E. J. Fetkovich and M. D. Fetkovich, “Useful Concepts for Decline-Curve Forecasting, Reserve Estimation, and Analysis,” *SPE Res Eng,* vol. 11, no. 1, p. 13–22, 1996.

[18] A. Clark, L. Lake and T. Patzek, “Production Forecasting with Logistic Growth Models,” in *SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA, 2011.

[19] A. Duong, “An Unconventional Rate Decline Approach for Tight and Fracture-Dominated Gas Wells,” in *Canadian Unconventional Resources and International Petroleum Conference.* , Calgary, Alberta, Canada, 2010.

[20] D. Ilk, J. A. Rushing, A. D. Perego and T. A. Blasingame, “Exponential vs. Hyperbolic Decline in Tight Gas Sands — Understanding the Origin and Implications for Reserve Estimates Using Arps' Decline Curves.,” in *Paper presented at the SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA, 2008.

[21] P. Valko, “Assigning value to stimulation in the Barnett Shale: a simultaneous analysis of 7000 plus production hystories and well completion records,” in *SPE Hydraulic Fracturing Technology Conference* , Woodlands, Texas. , 2009.

[22] M. Kumar, K. Swaminathan , A. Rusli and A. Thomas-Hy, “Applying Data Analytics & Machine Learning Methods for Recovery Factor Prediction and Uncertainty Modelling,” *SPE Asia Pacific Oil & Gas Conference and Exhibition,* Vols. SPE-210769-MS , pp. 1-12, 2022.

[23] N. Ibrahim, A. Alharbi, T. Alzahrani, A. Abdulkarim, I. Alessa, A. Hameed, A. Albabtain, D. Alqahtani, M. Alsawwaf and A. Almuqhim, “Well Performance Classification and Prediction: Deep Learning and Machine Learning Long Term Regression Experiments on Oil, Gas, and Water Production,” *Sensors,* vol. 22, no. 5326, pp. 1-22, 2022.

[24] P. Panja, W. Jia and B. Mcpherson, “Prediction of well performance in SACROC field using stacked Long Short-Term Memory (LSTM) network,” *Expert Systems With Applications* , vol. 205, no. 117670, pp. 1-25, 2022.

[25] Y. Dong, Y. Zhang and X. Cheng, “Reservoir Production Prediction Model Based on a Stacked LSTM Network and Transfer Learning,” *ACS Omega,* vol. 6, pp. 34700-34711, 2021.

[26] P. Yao, Z. Yu, Y. Zhang and T. Xu, “Application of machine learning in carbon capture and storage: An in-depth insight from the perspective of geoscience,” *Fuel,* vol. 333, no. 1, p. 126296, 2023.

[27] B. Chen, D. R. Harp, Y. Lin, E. H. Keating and R. J. Pawar, “Geologic CO2 sequestration monitoring design: A machine learning and uncertainty quantification based approach,” *Applied Energy,* vol. 225, no. 1, pp. 332-345, 2018.

[28] J. You, W. Ampomah, Q. Sun, E. J. Kutsienyo, R. S. Balch, Z. Dai, M. Cather and X. Zhang, “Machine learning based co-optimization of carbon dioxide sequestration and oil recovery in CO2-EOR project,” *Journal of Cleaner Production,* vol. 260, p. 120866, 2020.

[29] U. P. Iskander and M. Kurihara, “Long Short-term Memory (LSTM) Networks for Forecasting Reservoir Performances in Carbon Capture, Utilisation, and Storage (CCUS) Operations,” *Scientific Contributions Oil & Gas,* vol. 45, no. 1, pp. 35 - 50, 2022.

[30] M. Alsharif, M. Younes and J. Kim, “Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation: The Case Study of Seoul, South Korea.,” *Symmetry,* vol. 11, no. 2, p. 240, 2019.

[31] S. Siami-Namini, N. Tavakoli and A. S. Namin, “A comparison of ARIMA and LSTM in forecasting time series,” *17th IEEE international conference on machine learning and applications (ICMLA),* pp. 1394-1401, 2018.

[32] S. A. Ludwig, “Comparison of time series approaches applied to greenhouse gas analysis: ANFIS, RNN, and LSTM.,” *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE),* pp. 1-6, 2019.

[33] Y. Ning, H. Kazemi and P. Tahmasebi, “A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet,” *Computers & Geosciences,* vol. 164, no. 105126, 2022.

[34] A. Parasyris, G. Alexandrakis and G. Kozyrakis, “Predicting Meteorological Variables on Local Level with SARIMA, LSTM and Hybrid Techniques,” *Atmosphere,* vol. 13, no. 878, 2022.

[35] K. Greff, K. Srivastava, J. Koutnik, B. R. Steunebrink and J. Schmidhuber, “LSTM: A Search Space Odyssey,” *Transactions on Neural Networks and Learning Systems*, vol. 28, no. 10, pp. 2222-2232, 2016.

[36] G. Reikard, “Predicting solar radiation at high resolutions: A comparison of time series forecasts,” *Solar Energy*, vol. 83, no. 3, p. 342–349, 2009.

Manuscript with Track Changes Marked

Title: Utilisation of Artificial Intelligence based Time-Series Prediction to validate Carbon Containment in Injection Well in Illinois Basin

Authors: Munish Kumar[a] and Kannappan Swaminathan[b]

Affiliations: [a]Singapore University of Social Sciences, School of Business, Clementi Rd, #463号, Singapore 599494

[b]Insights Inc

Corresponding author. Email: munishkumar001@suss.edu.sg

Abstract:

~~Carbon Capture Utilisation and Storage (CCUS) involves capturing CO_2 emissions and securely storing them in geological formations. CCUS is gaining significance in global efforts to meet ambitious climate goals. The storage of CO2 typically occurs through injection into saline aquifers, depleted oil and gas fields, or for Enhanced Oil Recovery (EOR). However, all methods require a deep understanding of subsurface geology and the ability to monitor CO_2 behaviour during injection and storage.~~

~~Pilot projects like the Illinois Basin – Decatur Project demonstrated the practical feasibility of storing CO_2 underground. The injection spanned three years, during which nearly 999,215 tonnes of CO_2 was stored. Monitoring was carried out through a pair of wells equipped with sensors to track pressure and temperature at various depths.~~

This paper focuses on using time series injection data and monitoring information to predict changes in injection rates for the carbon ~~capture~~ sequestration well. The data we have used comes from the Illinois Basin - Decatur Project, a pilot CO_2 project that demonstrated the practical feasibility of storing CO_2 underground. The injection spanned three years, during which nearly 999,215 tonnes of CO_2 was stored. Data was recorded across a pair of wells equipped with sensors to track pressure and temperature at various depths.

Formatted: Strikethrough

Formatted: Subscript

We perform the prediction using Long Short-Term Memory (LSTM) neural networks (NN). These changes, represented as deltas (Δ or inj_diff) in injection rates between time t and time (t-1), are crucial indicators of carbon containment ~~and migration~~ within the well. By correlating these rate changes with other well parameters, this approach serves as a checkpoint against unwanted and unexpected carbon ~~migration~~ containment breaches or downhole losses during the injection process.

Formatted: Not Highlight

Our work aims to show that ~~M~~machine learning methods ~~are applied to~~can be useful to forecast these injection rate deltas based on monitoring data, thereby ~~validating~~ providing a way that is complimentary to traditional methods, to determine the effectiveness of carbon containment during injection.

One-Sentence Summary: Applying machine learning and predictive analytics via time series injection information and monitoring data on a carbon ~~capture~~ sequestration well to predict well injection rate deltas.

Keywords (minimum 6): low-carbon, time-series, neural network, LSTM, carbon capture, injection pressure, monitoring, ~~plume~~ migration

Introduction

~~Undoubtedly, human activities stand as a prominent cause behind the surge in greenhouse gas (GHG) emissions and the subsequent global warming. The escalation of carbon dioxide (CO_2) levels can primarily be attributed to swift industrialization and population expansion, which have only accelerated since the 1960s~~

The burning of ~~fossil fuels (such as~~ coal, oil, and natural gas~~)~~ has resulted in the generation of various greenhouse gases such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) ~~generation~~ [1]~~[1]~~. A report generated ~~by the United States Environmental Protection Agency (EPA) evaluated the amount of CO_2 generated in 2020 to be ~3.11 million metric tons~~Liu et al revealed that global CO_2 emissions for 2022 reached 36.1 $GtCO_2$ [2]~~[2]~~. Failure to effectively manage such substantial quantities will result in irreversible environmental consequences.

Carbon Capture Utilisation and Storage (CCUS) is one promising method to deal with the produced CO_2 from anthropogenic sources. The idea is to capture CO_2 from an emission point source and subsequent sequester it via injection into a suitable geological formation, with the explicit aim to store the CO_2 safely, in a state of permanence. CCUS is now being viewed as a key technology that will assist us in reaching increasingly ambitious global anthropogenic climate change goals. Typically, CO_2 geologic storage can be carried out in a number of different ways, including Enhanced Oil Recovery (EOR) processes, ~~CO_2 storage is carried out in one of three ways – via~~ injection into virgin saline aquifers or~~;~~ into depleted oil and gas fields~~; or if used for Enhanced Oil Recovery (EOR) processes~~. These methods all have different project drivers, risks, and commercial implications. However, what these ~~3~~ three methods have in common is the requirement that (a) there be a good understanding of the subsurface geological properties and (b) there be some ability to monitor and even predict CO_2 ~~migration~~containment behaviour at the well scale, be it during the injection phase or during the shut-in phase.

The importance of real-time CO_2 ~~migration~~containment monitoring in the subsurface

Formatted: Strikethrough

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Subscript

Formatted: Subscript

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Subscript

Evaluating CO_2 ~~migration~~containment is ~~hard to predict, given its dynamic nature and its interaction with geological formations. CO_2 behaviour in the subsurface is~~ a multiscale challenge, with measurement scales spanning orders of magnitude, from kilometres to nanometres. At the reservoir (kilometres to meters) scale, satellite-based remote sensing, 4D seismic monitoring, tiltmeters, downhole sensors and tracers deployed within injection wells can offer precise data on CO_2 distribution~~ and migration paths~~. At the centimetre to nanometre scale, geochemical monitoring of produced fluids provides insights into CO_2 interactions with subsurface formations.

The intermediate scale (meters to centimetre) is where conventional "well-based" measurements are conducted. These include the monitoring of CO_2 injection rates, well (annulus) pressures, casing pressure tests, and cased hole/production logging measurements. This enables a real-time assessment of CO_2 injection efficiency and potential leakage.

~~Given the early stage of this technique, it is imperative to initiate pilot development and validate the technology. The Illinois Basin – Decatur Project is one such study which aimed to demonstrate the capacity, injectivity, and containment of carbon storage in the Mount Simon Sandstone, the main carbon storage resource in the Illinois Basin and the Midwest Region. The source of the injected CO_2 is from ethanol production at the Archer Daniels Midland company's plant. The CO_2 is compressed, dehydrated and injected into the Mt. Simon Sandstone, which is primarily a saline aquifer approximately ~7,000 ft deep. Injection began in 2009 and continued for a 3-year period (Nov 2011 to Nov 2014). Cumulatively, ~999,215 tonnes of supercritical CO_2 have been injected and geologically stored. A pair of injection and verification wells, ~700ft apart, were drilled into the formation. The wells were equipped with downhole sensors to monitor pressure and temperature at various depths of interest.~~

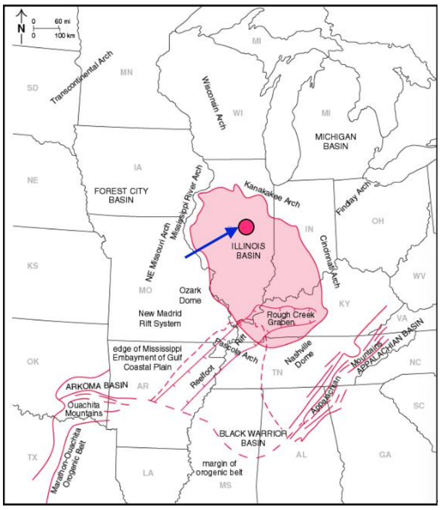
Formatted: Subscript

Formatted: Subscript

Formatted: Subscript

Formatted: Indent: First line: 0.2"

Formatted: Strikethrough



~~Figure 1: Location map of the Illinois Basin – Decatur Project (IBDP). Image taken from [3]~~

Formatted: Justified

Formatted: Normal, Line spacing: single

~~In general, such~~There have been documented instances where the abovementioned techniques have worked well in CO_2 ~~migration~~containment monitoring. One example is the Equinor operated Sleipner Project in the North Sea where the operator utilised seismic surveys and downhole pressure measurements to demonstrate effective containment~~ of the CO_2 plume~~ [4] ~~[4]~~. Yet, there are also documented instances where, despite extensive monitoring efforts, unexpected CO_2 leakage behaviour does occur. The In Salah project in Algeria, led by BP, Statoil, and Sonatrach, is one such example [5] ~~[5]~~. The latter underscores the importance of continual vigilance and timely adaptive management in CO_2 ~~CCUS~~containment ~~projects~~ to mitigate risks effectively.

Formatted: Subscript

Formatted: Subscript

Formatted: Subscript

The above examples illustrate that it is sometimes not enough to rely solely on hardware based solutions like ~~S~~sensor measurements at the monitoring well~~ are a much needed first line of defence but is not foolproof~~. Rather, we postulate that subtle fluctuations in injection rates can~~However,~~ act as a predicators for potential future containment breaches. By training a machine learning model to recognise these subtle fluctuations, potential containment breaches can be flagged prior to them occurring. If the model triggers in such events, the operator would simply need to shut the well in and investigate, for risk mitigation purposes.~~ if such sensor~~

~~measurements are coupled with machine learning algorithms, such that subtle patterns and anomalies can be detected, this may potentially act to mitigate risk further.~~

The Significance and Complexity of Optimising CO_2 Injection Rates

Achieving optimised CO_2 injection involves maximizing the rate and volume of CO_2 while ensuring it remains in a supercritical state, thereby minimising phase transitions, vaporisation, and hydrate formation from the wellhead to the injection point. This necessitates meticulous consideration of three primary parameters: reservoir heterogeneity, pressure, and time.

Reservoir heterogeneity, encompassing permeability, porosity, and lithology, significantly influences injection rates. High-permeability formations facilitate rapid CO_2 flow, while geological features such as layering, faults, and fractures can both enhance CO_2 distribution and affect injection rates. Injecting CO_2 too rapidly can induce skin effects, diminishing overall field injectivity. Moreover, reservoir pressure, inversely correlated with the volume of CO_2 injected, must be carefully managed to prevent overfilling, which can lead to seismic activity and potential CO_2 containment breach.

In essence, comprehending the intricate interplay between reservoir capacity and injection parameters is imperative for ensuring the efficiency and safety of CO_2 sequestration endeavours. This understanding extends to recognising the temporal dynamics of CO_2 injectivity and its relationship with various influencing factors over time. Through the analysis of historical CO_2 injectivity data and its correlation with time-sensitive parameters, engineers can refine reservoir management strategies via modeling and scenario analysis. This approach allows for informed decision-making regarding CO_2 storage and utilisation projects, ultimately advancing the efficacy and sustainability of carbon capture and storage initiatives.~~The importance and challenge of predicting CO_2 injection rates~~

Formatted: Subscript
Formatted: Heading 2, Indent: First line: 0", Line spacing: Double
Formatted: Font: Not Bold
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Font: Not Bold
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Font: Not Bold, Subscript
Formatted: Font: Not Bold
Formatted: Subscript
Formatted: Subscript
Formatted: Subscript
Formatted: Subscript
Formatted: Subscript

~~Operators are interested in the maximum rate at which CO_2 should be injected into the subsurface, as current climate models suggest large volumes of CO_2 need to be sequestered quickly to mitigate climate change effects. However, the determination of optimal rates of CO_2 injection is a challenge~~

~~Given that operators may want to have as high a rate as possible, what are the factors that actually determine the rate at which the operators are injecting CO_2 (e.g., the pressure rise in the aquifer, equipment malfunctions, etc)? This would be directly relatable to what you are predicting. Lastly, there should be a discussion about why AI can become a preferred method: among other things, some existing methods to estimate subsurface injection rates can become complex and/or costly when considering at a basin scale. I'm sure there are other reasons that can be stated as well. What are the other ways in which maximum injection rates are currently calculated? What are the tradeoffs in methods? There is often, no single right way of doing things.~~

~~This paper aims to use time series injection information and monitoring data on a carbon capture well to predict carbon capture well injection rates deltas (Δ) which is the difference in the injection rate (IR) at time t and time (t-1) i.e.~~

$$\Delta = IR_t - IR_{t-1} \quad \text{Equation 1}$$

~~CO_2 injectivity, or the rate at which CO_2 can be effectively injected into subsurface reservoirs, depends on a multitude of factors. Geological and reservoir parameters such as permeability, porosity, and lithology significantly influence injection rates. High-permeability formations facilitate faster CO_2 flow, while variations in reservoir characteristics, including layering, faults, and fractures, can impact CO_2 distribution and flow patterns. Reservoir heterogeneity must be carefully understood to accurately predict injection rates. Pressure management is crucial to prevent reservoir overpressurization, induced seismicity, or CO_2 leakage. Injecting too rapidly may fill the reservoir prematurely or cause skin issues, reducing injectivity. Additionally, maintaining CO2 in a supercritical state from the wellhead to the injection point minimizes phase transitions, vaporization, and hydrate formation, ensuring efficient injection. Injection pump and well design must also be optimized to handle the desired rate at pressure and temperature. Achieving optimum injectivity requires~~

Formatted: Highlight
Formatted: Subscript, Highlight
Formatted: Highlight
Formatted: Highlight
Formatted: Subscript, Highlight
Formatted: Highlight
Formatted: Font: English (Australia)
Formatted: Font: English (Australia), Subscript
Formatted: Font: English (Australia)
Formatted: Font: English (Australia), Subscript
Formatted: Font: English (Australia)
Formatted: Subscript
Formatted: Subscript
Formatted: Subscript

~~balancing these factors to maximize both rate and volume.~~ ~~Injecting too rapidly may fill the reservoir prematurely or cause skin issues, reducing injectivity.~~ ~~Therefore, a comprehensive understanding of reservoir capacity and injection parameters is essential to ensure efficient and sustainable CO_2 sequestration.~~

~~Correlating the change in injection rate to the behaviour of other parameters in the well can be used to provide a checkpoint against carbon migration from the well or other losses during the process. Utilisation of a machine learning (ML) method to predict injection rate deltas based on monitoring well data can be used to validate carbon containment throughout the injection of the well as well.~~

Literature Review

Various authors have tried numerous methods to forecast ~~future trends~~ based on ~~past data~~historical data. Work by De Gooijer and Hyndman [6]~~[6]~~, for instance, reviewed a series of time-series forecast models over a 25-year period, from 1985 to 2005. Their review highlighted various models being developed and applied in a myriad of scenarios related to finance, statistics and manufacturing, and included methods such as (a) exponential smoothing [7, 8] ~~[7, 8]~~, (b) Autoregressive Integrated Moving Average (ARIMA) [9]~~[9]~~, (c) seasonal models [10]~~[10]~~, (d) state space and structural models and the Kalman filter [11]~~[11]~~, (e) nonlinear models [12]~~[12]~~[12], (f) long-range dependence models, including the family of Autoregressive Fractionally Integrated Moving Average (ARFIMA) models [13]~~[13]~~, (g) Autoregressive Conditional Heteroskedasticity/Generalized Autoregressive Conditional Heteroskedasticity (ARCH/GARCH) models [14]~~[14]~~, and (h) count data forecasting [15]~~[15]~~.

Within reservoir engineering, ~~the prediction of~~the extrapolation of hydrocarbon and water recovery rates from geological formations into the future can be ~~attributed~~ viewed as a type of time-series forecasting ~~problem~~. Empirical solutions developed by Arps [16]~~[16]~~, referred to as decline curve analysis (DCA) technique is one of the earliest methods to address this problem. The method is based on a curve-fit principle, where one would attempt to fit either exponential, hyperbolic or harmonic curve to historical flow production rate as a function of time. Equation 1 shows the general form of the equation, while Equation 2 and Equation 3 are more specialised forms of the equation:

Formatted: Subscript

Formatted: Indent: First line: 0.2"

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Field Code Changed

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Field Code Changed

Formatted: Font: English (United States), Do not check spelling or grammar

General Form (Hyperbolic Decline)	$$q(t) = \frac{q_i}{(1 + bD_i t)^{1/b}}$$	Equation 1
Exponential Decline	$$q(t) = q_i\, e^{-dt}$$	Equation 2
Harmonic Decline	$$q(t) = \frac{q_i}{(1 + bD_i t)}$$	Equation 3

where q_t is the flow rate at time t (bbls/day), q_i is the initial flow rate (bbls/day), t is time (day), D_i is the initial decline rate (%~~units~~), ~~-~~and b is the degree of curvature of the line (Arps' decline-curve exponent). ~~An exponential curve fit would have b = 0, a~~A hyperbolic curve would have 0 < b < 1 and a harmonic curve would have b = 1. The fitted curve is then used to predict future production rates and cumulative production [17]. This method was originally designed to work with high porosity-permeability reservoirs and tends to overestimate hydrocarbon recovery from unconventional (low permeability) reservoirs. Thus, various authors have tried to expand on this work [18, 19, 20, 21]~~[17, 18, 19, 20][17, 18, 19, 20]~~, and are mostly variations of the initial DCA method developed by Arps. For an effective DCA forecast, domain and field knowledge ~~is~~are key, but inherently the process is one of trial and error, and thus it is not uncommon for DCA results to have 'low-best-high' estimates.

With the advent of big data, fast computing and cheap memory, applying a machine learning (ML) and artificial intelligence (AI) solution for time-series forecasting seems a natural evolution. ML solutions were first introduced to the petroleum industry in the early 2000s. Applications of ML and AI include addressing prediction of reservoir parameters [22]~~[21]~~, history matching, of oil, gas and water production forecasting (flow rate prediction), pattern recognition in well logs and well tests analysis, production enhancement and prediction of failures, among others [23, 24, 25]~~[22, 23, 24]~~.

~~In the field of CCUS and injector production performance, there is little to no available data related to time series and forecasting. This can be attributed to the early stages of development of both domains. Literature~~

Formatted Table
Formatted: Centered
Formatted: Centered
Formatted: Centered
Formatted: Subscript
Formatted: Highlight
Formatted: Font: English (United States), Do not check spelling or grammar
Field Code Changed
Formatted: Font: English (United States), Do not check spelling or grammar
Formatted: Font: English (United States), Do not check spelling or grammar
Formatted: Font: English (United States), Do not check spelling or grammar
Formatted: Font: English (United States), Do not check spelling or grammar

~~appears to be mostly concentrated in~~ML algorithms have been used to predict~~ing~~ carbon emissions [23], leakage [24], CO_2 absorption and adsorption [25], property prediction and process simulation [26], simulation of transportation, and geological behaviours as it relates to uncertainty analysis, sequestration, utilisation and EOR processes [26, 27, 28]~~[25, 26, 27]~~. In the field of CCUS and well performance, ~~W~~ work by Iskander et al [29]~~[28]~~ employs Long Short-Term Memory (LSTM) networks to forecast oil, water and CO_2 production at future infill well locations, for both single phase and 3-phase fluid models. Data ~~was~~ were in the form of a synthetic PUNQ-S3 reservoir model, combined with real-world observations from 8 production wells, which recorded daily production volumes over a decade from 2004-2014 [29]~~[28]~~. Injection data from CO_2 wells was not a direct input in the deep learning model, although it did play an indirect role in the oil and gas production data being recorded, as it swept the residual hydrocarbons and therefore resulted in an uplift in production rates.

We aim to develop on the work of Iskander and others by utilising ML and AI methods, and in particular LSTM, but focusing on the prediction of CCUS injection well performance, using the open-source information from the IBDP (Illinois Basin ~~-~~ – Decatur Project) [3]~~[3]~~. We will demonstrate how our developed LSTM model shows a correlation between the change in injection rate to the behaviour of other dynamic parameters [29]~~[28]~~.

One of the objectives of the model is to detect anomalies and alert operators to closely inspect the wells for potential leaks. While still adhering to local jurisdictional requirements of well annulus pressure monitoring, periodic pressure tests and cased hole logging, ~~While the primary purpose of t~~ahe ~~he~~ ML model ~~is as a~~can be an additional method utilised to ~~checkpoint against~~ detect unexpected carbon ~~migration~~leaks~~, either at the well location or from other losses during the injection process.~~, ~~we~~ We also view the model as another means for engineers to perform scenario based de-risking of exploration plays, via modelling variations in well and storage parameters to validate CO_2 containment. The model will also aid in the understanding of the injection process and potentially can be used to "right size" injection rates, well operations and optimise costs.

Formatted: Subscript

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

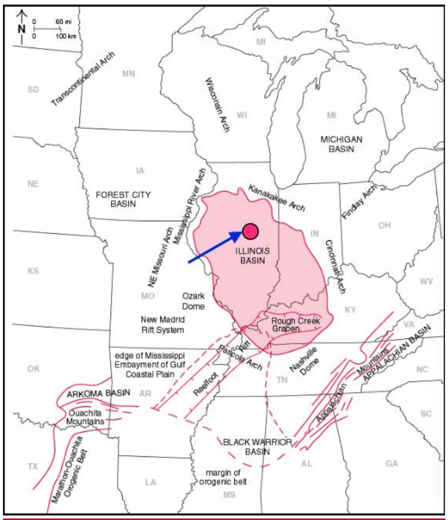
Formatted: Font: English (United States), Do not check spelling or grammar

Scope and Methods

This paper aims to use time series injection information and monitoring data on a carbon sequestration well to predict carbon sequestration well injection rates deltas (Δ or inj_diff) which is the difference in the injection rate (IR) at time t and time (t-1) i.e.

$$\Delta = IR_t - IR_{t-1} \qquad \text{Equation 4}$$

Our primary source of data is from the Illinois Basin - Decatur Project, a CO_2 pilot project meant to demonstrate the capacity, injectivity, and containment of carbon storage in the Mount Simon Sandstone, the main carbon storage resource in the Illinois Basin and the Midwest Region (Figure 1(L)). The source of the injected CO_2 is from ethanol production at the Archer Daniels Midland company's plant. The CO_2 is compressed, dehydrated and injected into the Mt. Simon Sandstone, which is primarily a saline aquifer approximately ~7,000 ft deep. Injection began in 2009 and continued for a 3-year period (Nov-2011 to Nov-2014). Cumulatively, ~999,215 tonnes of supercritical CO_2 have been injected and geologically stored. A pair of injection and verification wells, ~1007ft apart, were drilled into the formation (Figure 1(R)). The wells were equipped with downhole sensors to monitor pressure and temperature at various depths of interest.



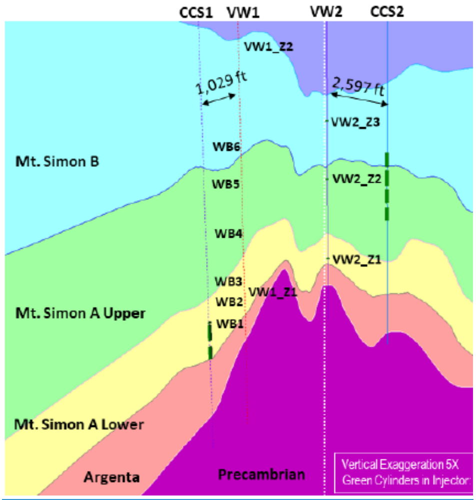


Figure 1: (L) Location map of the Illinois Basin – Decatur Project (IBDP). ~~Image taken from~~ [3](R) Schematic illustration of the formation layers, location of perforation intervals in the CCS1 injector well (green cylinders) and the location of the verification well (VW1). Image taken from [3]

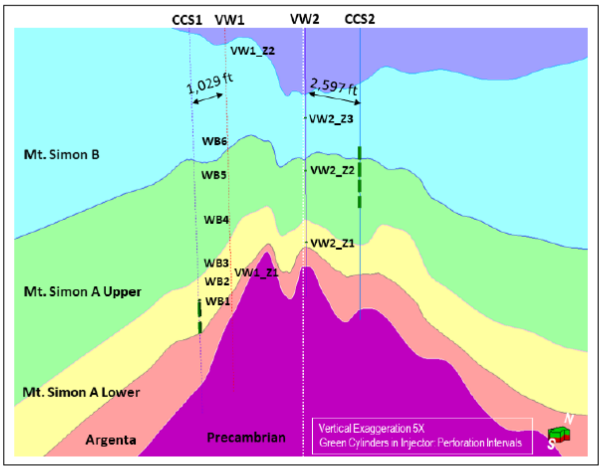


Figure 69. Location of perforation intervals in injectors (green cylinders) and pressure gauges in monitoring wells along the cross- sections I-I' (left) and II-II' (right).

~~Ref : Static_Model_Report~~

Formatted Table

Formatted: Font: English (United States), Do not check spelling or grammar

Formatted: Centered

Formatted: Centered, Line spacing: Double

~~Figure 2 depicts the formation layers, CC1 – Injection well and the VW1, which is the verification well. It also shows the perforations in the injection well in relation to the sensors at the VW1.~~

Formatted: Normal, Line spacing: single

Datasets

During this three-year period, a substantial amount of data was collected from both an injection and monitoring well, 1007~~700~~ ft apart. The injection well was drilled to a total depth (TD) of ~~~7051~~ 7238 ft, and was drilled with a 26” bit to 355 ft, and cased with a 20” casing to surface. A 17 ½” hole size then followed to a TD of 5339 ft, and an intermediate casing string 13 3/8” in diameter was set. The reservoir section was drilled in a 12 ½” hole size to ~ 7056 ~~ft, and~~ft and completed with a 9 5/8” production casing and 4 ½” tubing. The perforations were made at the base (i.e. above the ~~p~~Pre~~-C~~cambrian) Mt. ~~St~~ Simon Sandstone, which was a relatively thick reservoir of ~1620 ft. A total of 3 geophones were set at 4925 ft, 5743 ft and 6137 ft along with a pressure / temperature gauge mandrel at 6325 ft. The monitor well was drilled to a total TD of 7272 ft; it had a surface casing (13 3/8” to 377 ft, followed by intermediate casing of 9 5/8” to 5322 ft and 5 ½” casing across the Mt. St Simon Sandstone, which contained a 3 component geophone array) [3]~~[3]~~.

Field Code Changed

Formatted: Font: English (United States), Do not check spelling or grammar

A. Data Collection and Preparation

A total of 34 parameters were measured from the injection and verification well. The parameters measured comprised of both surface and downhole measurements which were acquired at five second intervals over three full years. The sheer volume of data required that the time scale be downscaled to hourly intervals, taking the parameter average over the hour. 27,665 hours of data (training data) was used to build a suitable model. 67% of the “training” data set was used to train the model. The remaining 33% was used as a “validation” dataset. The model built off this data was finally used to predict 201 hours of Δ into the future (“hold out” data). Given in Table 1 is the descriptive statistics of the provided data; we refer readers to the nomenclature table for the definition of the variables. We note that there are a series of “null values” (including negative null values) and non-numeric numbers, missing rows, time gaps and note that for some of the input data measurements, there are significant outliers.

Table 1: Data Statistics

Measurement	Non-Zero Value	Mean Value	Standard Deviation	Minimum Value	25th Percentile	Median Value	75th Percentile	Maximum Value
Avg_PLT_CO2VentRate_TPH	27398.0	2.1	133.2	0.0	0.0	0.1	0.2	18333.2
Avg_CCS1_WHCO2InjPs_psi	27270.0	1239.9	817.7	0.0	1235.5	1338.9	1361.0	39032.4
Avg_CCS1_WHCO2InjTp_F	27398.0	89.8	48.3	0.0	93.0	96.3	96.9	2879.4
Avg_CCS1_ANPs_psi	27304.0	560.9	445.9	0.0	523.5	564.9	604.8	24105.6
Avg_CCS1_DH6325Ps_psi	27398.0	3244.2	173.5	0.0	3233.0	3286.1	3324.7	3515.9
Avg_CCS1_DH6325Tp_F	27398.0	127.7	7.2	0.0	127.2	130.1	131.1	135.7
Avg_VW1_WBTbgPs_psi	26127.0	1801.8	999.4	0.0	2173.5	2322.4	2379.8	4954.7
Avg_VW1_WBTbgTp_F	26061.0	80.8	44.3	0.0	103.4	104.2	105.0	120.1
Avg_VW1_ANPs_psi	23487.0	525.0	3988.7	0.0	0.5	4.7	16.9	31993.5
Avg_VW1_Z11D4917Ps_psi	26688.0	1597.5	873.3	0.0	2070.3	2073.4	2074.1	2378.0
Avg_VW1_Z11D4917Tp_F	26709.0	81.7	44.2	0.0	103.7	105.2	106.5	108.6
Avg_VW1_Z10D5001Ps_psi	26688.0	1627.9	889.9	0.0	2106.9	2112.4	2116.6	2420.6
Avg_VW1_Z10D5001Tp_F	26709.0	81.2	44.0	0.0	101.8	104.7	105.0	110.9
Avg_VW1_Z09D5653Ps_psi	26688.0	1961.1	1071.9	0.0	2534.0	2547.5	2551.1	2785.4
Avg_VW1_Z09D5653Tp_F	26709.0	87.4	47.3	0.0	111.5	112.8	113.5	114.9
Avg_VW1_Z08D5840Ps_psi	26189.0	1604.8	1289.3	0.0	0.0	2627.3	2637.4	4446.2
Avg_VW1_Z08D5840Tp_F	25878.0	69.0	56.4	0.0	0.0	114.0	115.0	353.2
Avg_VW1_Z07D6416Ps_psi	25985.0	2199.2	1273.0	0.0	0.0	2911.6	2925.3	3195.0
Avg_VW1_Z07D6416Tp_F	25985.0	88.8	50.8	0.0	116.5	116.9	118.6	145.1
Avg_VW1_Z06D6632Ps_psi	25500.0	2315.6	1308.6	0.0	3012.2	3026.1	3031.3	3380.4
Avg_VW1_Z06D6632Tp_F	25500.0	90.9	50.8	0.0	116.6	118.6	119.4	124.3
Avg_VW1_Z05D6720Ps_psi	23955.0	2106.0	1447.2	0.0	0.0	3069.6	3073.6	3365.9
Avg_VW1_Z05D6720Tp_F	23955.0	82.3	55.0	0.0	0.0	118.5	119.4	122.1
Avg_VW1_Z04D6837Ps_psi	26600.0	2347.5	1369.0	0.0	0.0	3148.0	3153.5	3331.9
Avg_VW1_Z04D6837Tp_F	26600.0	91.0	51.6	0.0	118.8	119.5	119.9	125.8
Avg_VW1_Z03D6945Ps_psi	24361.0	2350.9	1495.7	0.0	0.0	3299.9	3320.6	3457.9

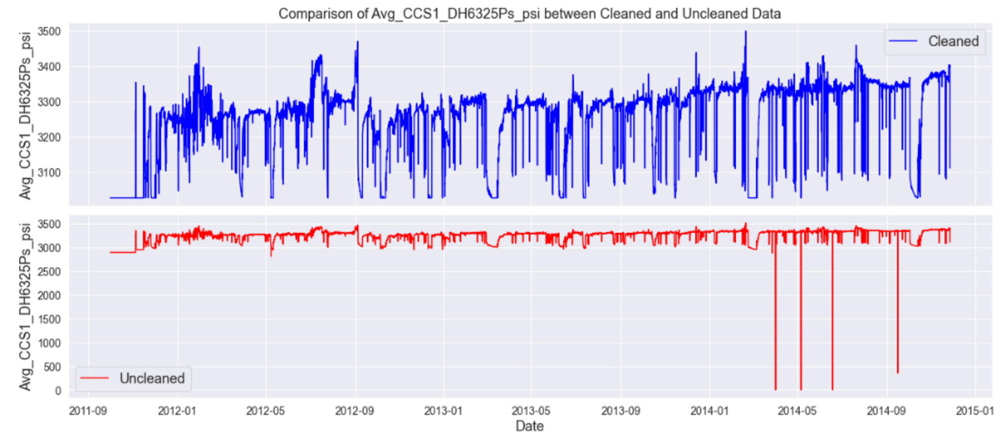
Avg_VW1_Z03D6945Tp_F	25932.0	182.3	368.5	0.0	0.0	121.3	122.8	1602.9
Avg_VW1_Z02D6982Ps_psi	26423.0	2456.6	1459.1	0.0	0.0	3316.2	3332.0	3499.6
Avg_VW1_Z02D6982Tp_F	26423.0	91.3	52.7	0.0	32.0	121.3	122.0	124.3
Avg_VW1_Z01D7061Ps_psi	25307.0	2300.2	1521.4	0.0	0.0	3318.2	3327.3	3445.1
Avg_VW1_Z01D7061Tp_F	25108.0	85.9	55.4	0.0	0.0	121.4	122.6	133.9
Avg_VW1_Z0910D5482Ps_psi	26709.0	1855.6	1017.6	0.0	2353.3	2374.9	2416.1	2758.3
Avg_VW1_Z0910D5482Tp_F	26709.0	86.3	46.7	0.0	110.5	111.5	112.0	113.7
inj_diff	27397.0	0.0	82.7	-11021.1	-0.1	0.0	0.1	7033.5

B. Cleaning Data

We reviewed the attributes for the data, and were especially concerned about discontinues, non-numerical data or data that were clearly outliers (e.g. ~25,000 psi WHP at injection well or 0 psi downhole gauge pressure). We utilised ~~3~~ 4 methods to clean the data, in order of operation (i) we firstly performed a computational fill of all the missing and null values with a “forward fill’ operation, with the last valid observation being propagated forward. We do this on the assumption that missing values retain the properties of the previous cell i.e. there has been no change in the data between time *t* and time (*t-1*), (ii) a Z-score method where

$$Z = \frac{x_i - \tilde{x}}{MAD} \qquad \text{Equation 5}$$

x_i is a single data value, $\tilde{x}$ is the median of the data set and MAD is the median absolute deviation of the dataset, (iii) removing values of formation pressure ~~and~~ that we know to be technically invalid and (~~iii~~iv) a final visual check of the data, removing outliers that we view as being deleterious to the interpretation. Shown in Figure 2 is an example of the impact that data cleaning has on the data quality. We see that our process has removed spikiness in the data and smoothed out some of the small-scale perturbations, resulting in a more manageable dynamic range.



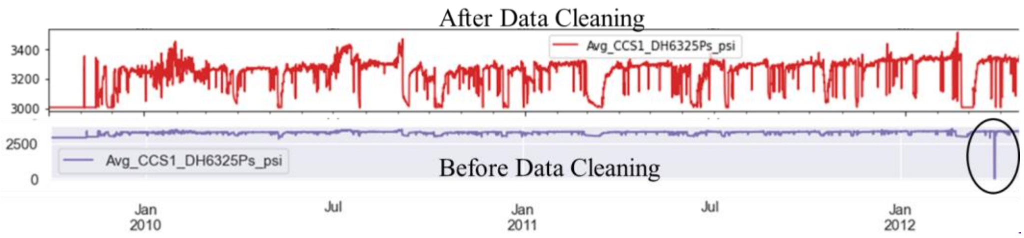


Figure 2: An example of the measurement before (lower image) and after (upper image) data ~~cleaning~~cleaning.

C. *Machine Leaning Model Selection - Long Short-Term Memory (LSTM) vs. Autoregressive Integrated Moving Average (ARIMA)*

In the choice of ML model to apply, we had to decide between a statistical approach based on ARIMA, or alternatively, the use of a non-linear algorithm such as neural networks (NN). Many authors have investigated comparing such methods and in various fields. What we noted from our review of the work was there was a general agreement that approaches like ARIMA would not only require less inputs, but would be less of a "black-box", which NNs are known to be [30, 31, 32]~~[29, 30, 31]~~.

ARIMA has been applied by previous authors to forecast oil production data [33]~~[32]~~. The "autoregressive" piece of ARIMA deals with finding a correlation between a specific value and a prior/lagged value, essentially seeing if a variable has any correlation to its past values. The “integrated” piece deals with making data stationary, essentially ensuring that properties of the data (such as mean and variance), are constant over time. The “moving average” piece of the model finds the dependency between a specific value, and the error from a moving average model applied to previous values. ARIMA models are therefore useful in forecasting time series data and are especially useful when trying to predict time series data that is non-stationary. While Ning et al observed that ARIMA was robust in predicting rates of oil production across wells, our review of ARIMA models being produced with high frequency data, where accuracy on an hourly basis was important, found that the error rate compounds significantly when the forecasting horizon is extended beyond a day [34]~~[33]~~.

LSTM is a type of recurrent NN which uses useful patterns from sequential data to provide accurate forecasts [23]~~[22]~~. It learns from previous outputs to provide better results the following time. A typical LSTM has 3 layers (i) an input gate which assigns weights based on the significance of different variables, (ii) a forget gate to retain only useful information, and (iii) an output gate which manages the information flow. LSTM holds a memory cell (known as a cell state) which retains captured information over longer time periods and preserves useful constituents using its input and forget gates, hence avoiding the vanishing gradient issue associated with traditional NNs. LSTMs are particularly useful for non-linear problems where there does not appear to be strict mathematical relationships between variables. Unlike recurrent NNs, LSTMs ~~are able to~~can account for long-term temporal effects without encountering optimisation hurdles like vanishing gradients [35]~~[34]~~. In our review of LSTM vs ARIMA models, we have found a common consensus in various fields that LSTM performed better, with reduced error rates but with significantly increased processing time [32, 31]~~[31, 30]~~.

Formatted: English (United States), Do not check spelling or grammar

Formatted: English (United States), Do not check spelling or grammar

Formatted: Font: English (United States), Do not check spelling or grammar

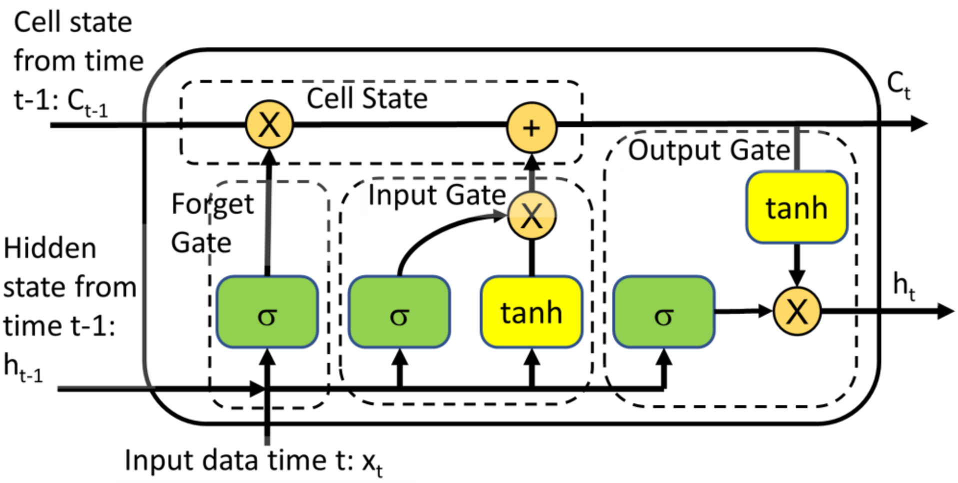


Figure 3: Schematic of LSTM network

We settled on the choice of LSTM because we realised that the data we were analysing was likely to contain non-seasonal, high frequency information, where accuracy was going to be important [36]~~[35]~~. Additionally, the were numerous variables provided which we did not know the relative importance of in prediction without a working model.

D. Model Performance and Hyperparameter Optimization

We access the model performance using a host of measures, from training and validation loss to mean absolute error (MAE - Equation 6), mean squared error (MSE - Equation 7), root mean squared error (RMSE - Equation 8) and the coefficient of determination (R^2 - Equation 9). The training and validation loss functions serve to determine how well the model is performing and to prevent overfitting. During training, the model learns by iteratively adjusting its parameters to minimize a defined loss function. The training loss measures the discrepancy between the model's predictions and the actual target values on the training data. The goal is the minimization of this loss, as it indicates how well the model is fitting the training data. The validation loss is the other component of this and is computed by evaluating the model's performance on a separate validation dataset, not used for training. It serves as an estimate of how well the model generalizes to unseen data.

Formatted: English (United States), Do not check spelling or grammar

MAE:	$\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - x_i\rvert$	Equation 6
MSE:	$\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2$	Equation 7
RMSE:	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$	Equation 8
R^2:	$1 - \frac{\sum(y_i - x_i)^2}{\sum(x_i - \bar{x})^2}$	Equation 9

Formatted Table

Equation 6 to Equation 9 show the other measurement metrics, with y_i as the predicted value, x_i as the true value, $\bar{x}$ as the mean of x_i and n as the total number of data points. MAE measures the average absolute difference between the predicted and actual values and provides an absolute measure of the model's performance. MSE measures the average squared difference between the predicted and actual values and amplifies larger errors due to the squaring operation. RMSE is the square root of MSE and provides a measure of the average magnitude of errors. It is useful for interpreting errors in the same units as the target variable. R^2 measures the proportion of the variance in the target variable that is explained by the model. It ranges from 0 to 1, where 1 indicates a perfect fit and 0 indicates a poor fit.

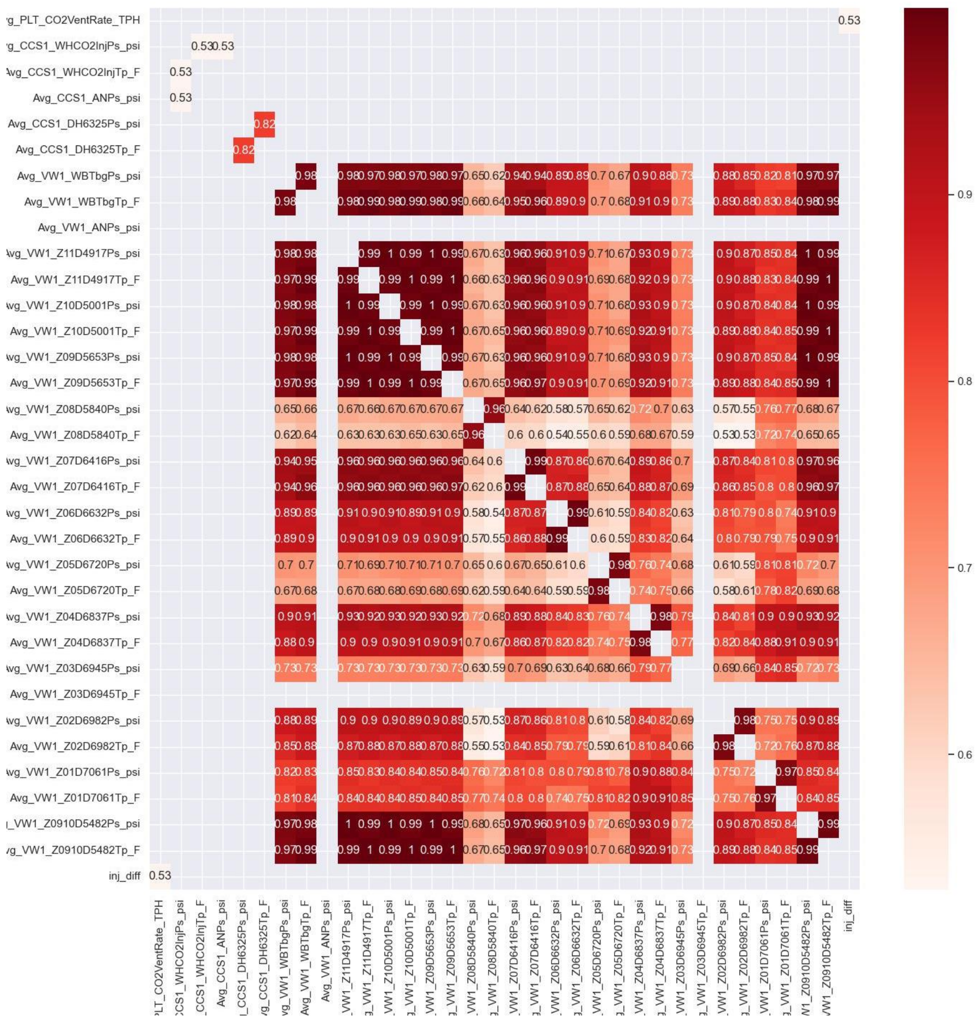
While MAE, MSE, RMSE, and R^2 are evaluation metrics used to assess the model's performance after training, the (training and validation) loss functions are specific to the training process. These loss functions guide the model's learning by providing gradients for updating the model's parameters. However, the suitability of the model is ultimately guided by scores where the MAE, MSE and RMSE and low, while the R^2 is high.

The NN model is tuned by varying a series of “hyperparameters”. A hyperparameter is a characteristic of a model that is external to the model and whose value cannot be estimated from data. The hyperparameters that were optimized included the (i) learning rate, (ii) the epochs, (iii) the number of neurons, (iv) the magnitude of dropout, (v) batch size, (vi) the choice of optimiser and finally (vii) the choice of activation function. To account for idiosyncrasies in the data (noise, patterns, outliers, etc.), k-fold cross-validation was run to validate the stability of the model.

Results and Discussion

Data Preparation

We observed significant collinearity of > 0.8 across most of the data set. Most were paired couplet measurements of "Temperature" and "Pressure" at various gauge depths. Keeping both parameters adds no additional information to the predictive model and in fact may be detrimental, with potential overfitting. Therefore, a single element from each of the variable pairs is eliminated to allow for a more stable model. Exceptions were made if variables were found to be from different sources e.g. tubing and reservoir pressure at the observation well for instance. This is also in line with conventional reservoir engineering concepts where temperature and pressure are correlated.



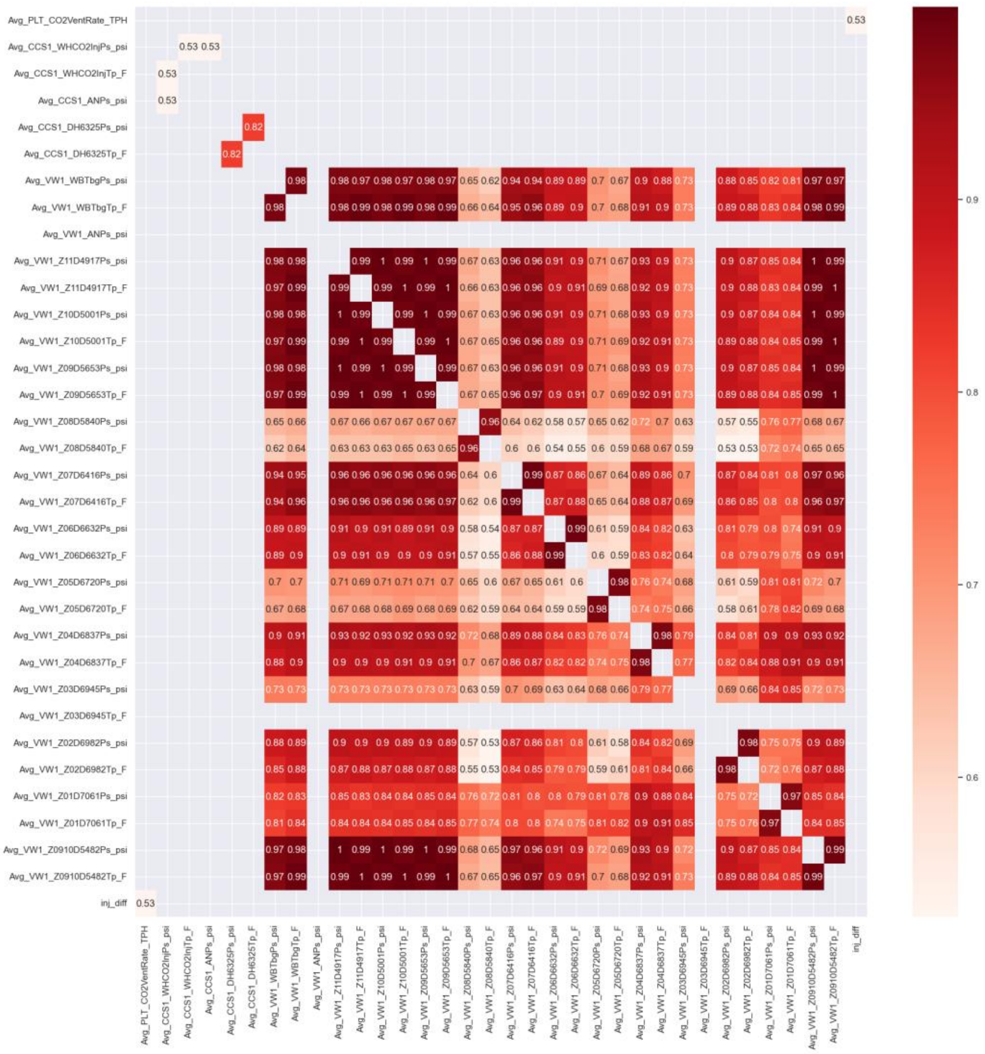


Figure 4: Correlation Matrix – Pairwise Correlation. It ranges from -1 to 1, -1 being a perfect negative correlation and +1 being a perfect positive correlation. The color scale visually depicts this: dark/warm show strong correlations

Formatted: Justified

Formatted: para1, Line spacing: Double

Excluding the target injection delta variable, ~~six~~ eight variables were retained for the machine learning application and are summarised in Table 2 for the entire dataset. All data is numerical data types. The total data size is 27,665 values per column, for a total of 248,784 data points which was approximately ~26% of the original data base.

Table 2: Statistics of the cleaned dataset

Measurement	Non-Zero Value	Mean Value	Standard Deviation	Minimum Value	25th Percentile	Median Value	75th Percentile	Maximum Value
Avg_PLT_CO2VentRate_TPH	27,665	1.015	3.94	0	0	0.06	0.15	60
Avg_CCS1_WHCO2InjPs_psi	27,665	1253	191	701	1233	1339	1361	1882
Avg_CCS1_WHCO2InjTp_F	27,665	91	12	59	93	96	97	120
Avg_CCS1_ANPs_psi	27,665	554	102	149	523	565	605	977
Avg_CCS1_DH6325Ps_psi	27,665	3254	106	3006	3234	3286	3326	3516
Avg_CCS1_DH6325Tp_F	27,665	128	4.58	117	127	130	131	136
Avg_VW1_WBTbgPs_psi	27,665	2248	452	60	2233	2343	2421	4817
Avg_VW1_Z05D6720Ps_psi	27,665	3043	233	282	3061	3072	3075	3366
inj_diff	27,665	0.03	3.74	-38	-0.08	0	0.07	38

LSTM Model Architecture

We have employed a stacked LSTM architecture, with 2 layers, for this evaluation. In a stacked LSTM model, the output sequence of one LSTM layer serves as the input sequence for the next LSTM layer in the stack. This allows for a hierarchical representation of the input data, with each LSTM layer capturing different levels of abstraction or temporal dependencies. The second layer of the stacked model feeds the results to the output layer. We also use dropout to reduce the risk associated with overfitting. Finally, there is a dense layer which predicts the output, a single timestep at a time.

We tested the performance of the model by varying the hyperparameters given in Table 3. We utilised K-fold cross validation for hyper parameter tuning, ensuring that we kept the time series harmony. By this, what we mean is we split the time series sequence into samples but retained the sequence of information. With each split, a model is trained using (k-1) folds of the training data. The model is then validated against the remaining fold. A final model is scored on the held-out fold, with scores averaged across the splits. We used this to refine our hyperparameters, and finally took an average of values you see in Table 3.

Each hyperparameter serves a specific purpose and it is fundamentally an iterative process to tune these parameters such that the model outputs are optimised. We broadly define each hyperparameter here, sharing more details in Table 3. The same table also shows our final selected values based on an optimised MSE value.

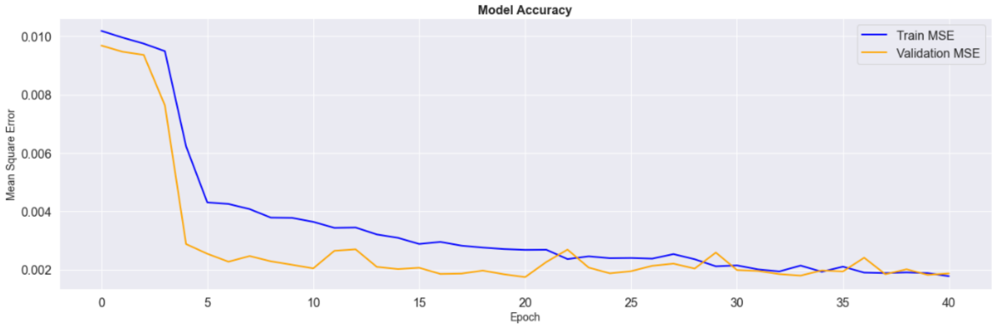
The learning rate refers to the model's degree of responsiveness to errors. Epochs refer to the number of iterations across the entire dataset, while neurons are the fundamental nodes/building blocks used to process inputs. Dropout refers to the proportion of randomly selected neurons which get deactivated (to prevent overfitting) and batch size addresses the quantity of inputs processed before updating the model. An optimiser algorithm is needed to minimize the loss function, by finding the optimal set of parameter values that lead to improved network performance. Finally, the activation function is a mathematical function which introduces non-linearity to the layer of neurons.

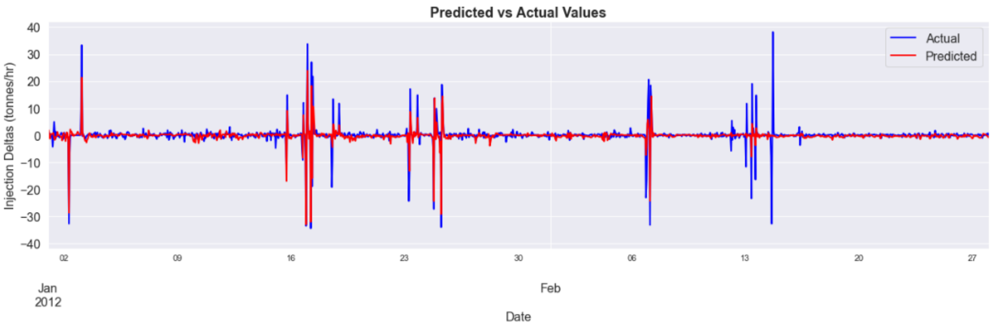
Table 3: Variation in Hyperparameter Values, Final Selected Values and Parameter descriptor

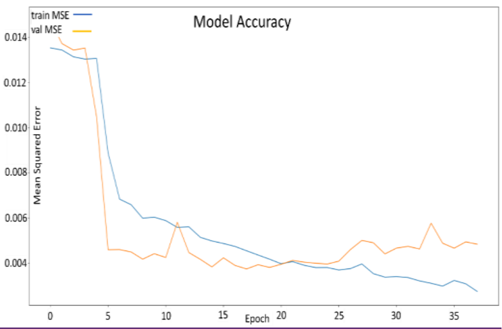
Measure	Minimum	Maximum	Final	Parameter Descriptor
Learning Rate (lr)	0.001	0.1	0.01	The rate at which the parameters (weights and biases) of the network are updated during the training process. It essentially controls how quickly or slowly the network learns from the gradients of the loss function.
Epochs	10	100	50	This parameter determines how many times the learning algorithm will iterate over the entire training dataset. Each iteration has the following steps (a) forward propagation, (b) loss computation, (c) backpropagation,

				and (d) update. These steps are repeated in the training dataset until all samples have been processed. This completes one epoch.
Neurons	10	50	20	Each neuron takes multiple inputs, performs a computation on those inputs, and produces an output. The computation typically involves applying a weighted sum of the inputs, followed by the application of an activation function.
Dropout	0.1	0.25	0.25	This parameter introduces noise or randomness into the network by temporarily removing a portion of the neurons from the calculation in each training iteration. By doing so, dropout prevents complex co-adaptations between neurons, reducing the reliance of the network on specific neurons and promoting the learning of more robust and generalized representations.
Batch Size	30	100	50	This parameter refers to the number of training examples that are processed together in a single forward and backward pass during training.
Optimiser	-	-	Adam	ADAM (Adaptive Moment Estimation) is an optimization algorithm used to update the weights of neural networks during the training process. It automatically adjusts the learning rate for each parameter based on the history of gradients. This was chosen as the default optimizer as it has the ability to converge quickly as well
Activation	-	-	tanh	The hyperbolic tangent function maps the input to a value between -1 and 1. It has an S-shaped curve like the sigmoid function but is symmetric around the origin. The formula for tanh is: $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

Figure 5 shows the MSE output of the training (train) and validation (val) sets for one of our K-folds. MSE is on the y-axis and epoch is on the x-axis. We observe the convergence between train and val, telling us that the model accuracy is improving per epoch. The point of convergence is arrived at by gradient descent and tells us the point of minimum information loss. In this example, we achieved convergence at around epoch = 30, with losses increasing beyond that.







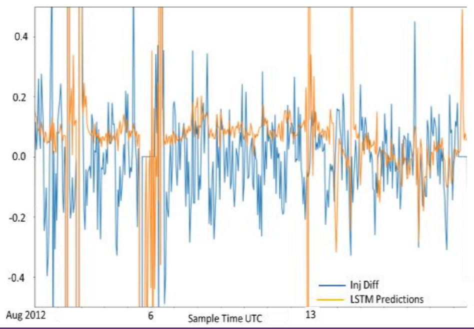


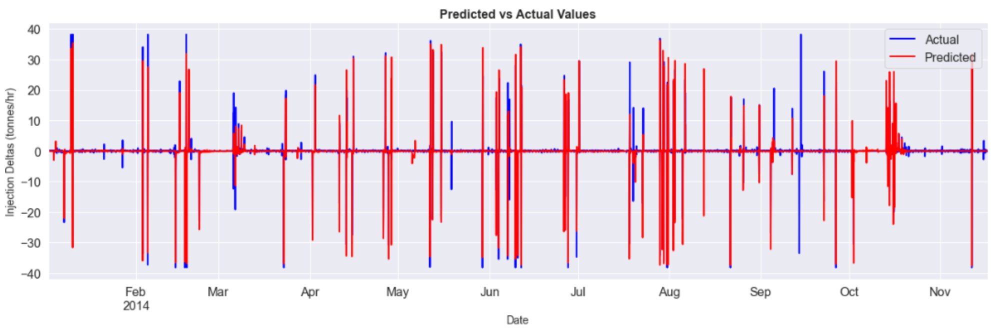
Figure 5: (~~a~~Upper) MSE output of the training and validation set (~~b~~Lower) Check file of a small subset of data; output from the K-fold set.

Formatted: Left

Prediction on Validation Data

We deployed our developed model on our ~~hold out~~validation data. Given in Figure 6 is the comparison between the predicted injection rate deltas versus the actual injection rate deltas in our validation set. The results demonstrate the model's capability to successfully identify and replicate actual anomalies, which provides evidence that the model is predictive in nature. Moreover, Figure 6 illustrates that the model ~~is able to~~can accurately capture both large scale high frequency signal, as well as smaller scale fluctuations in the injection deltas (admittedly, the subtle variations are harder to capture as these change at ranges of ± 1psi and can be described to be in the domain of “noise”), indicating the robustness of the LSTM model.

The fact that the model can capture both large and small-scale measures ~~strengthens~~strengthen our view that the model is indeed reliable in handling the variety of conditions experienced in the field during CO_2 injection, and hints at its ability to effectively mimic the intricate patterns found within field injection rate data. The successful reproduction of significant anomalies as well as subtle variations highlights the model's potential to provide valuable insights and reliable predictions in this domain.



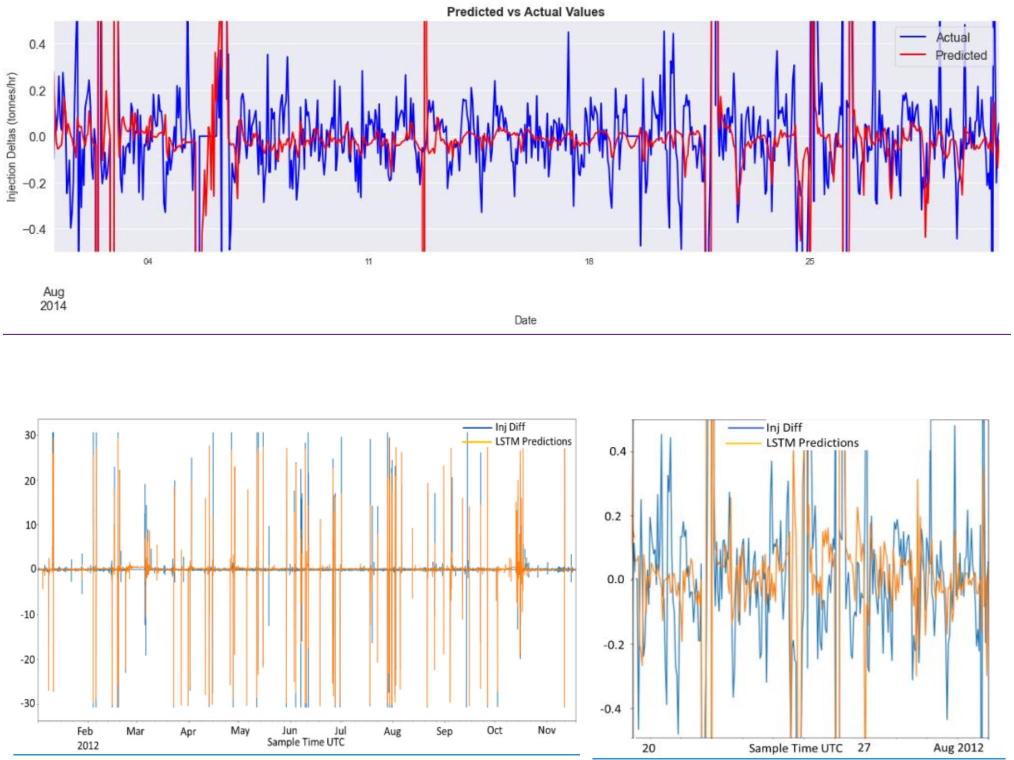


Figure 6: (~~a~~Upper) Able to match anomalies in injection delta (~~b~~Lower) Able to mimic the small variations in the injection delta.

Generalising the model

This LSTM model was built from (what is fundamentally) a single data set i.e. from a specific geological rock type, whose CO_2 flow behaviour is constrained by its own petrophysical and reservoir engineering properties. We think further generalisation of the model is necessary to truly confirm these findings. As we do not have data from other geological settings, we attempted generalisation through a series of sensitivity runs. We did this in 2 ways (a) selecting a single seed value but varying the input parameters fed into the model and (b) by randomising the seed value itself but keeping the input parameters constant.

(a) Single Seed, Variable Inputs

We used a single seed value (2250) but varied six of the selected as a test for model generalisation. Our first iteration (Run 1 in Table 4) is with a default hyperparameter setting, where the predicted injection delta is zero for all test timesteps; this yielded an RMSE value of 5.54 (Run 1 in Table 5).

Several adjustments were made to the inputs from that base case defined in run 1. These modifications included (a) scaling all columns within a range of -1 to 1 (runs 2 to 6), (b) replacing, as one of the input variables, the VW DH Z09 sensor with the VW DH Z05 sensor (runs 4 to 6), (c) incorporating well head pressure (WHP) sensor data (runs 2 to 4, run 6), (d) using temperature sensor data (runs 5 and 6), (e) increasing the Z-score band for the target column from 20 to 25 (runs 3 to 6), and (f) utilizing corrected values of zero for the VW DH sensor (runs 3 to 6).

By analysing the results of these runs and comparing them to the base and default settings, it is possible to determine the most optimal configuration that yields improved accuracy and reliability in predicting injection deltas. This series of sensitivity runs showed us that the model performs most optimally based on the configuration in run 6. It additionally tells us that the model is sensitive to scaling, and our Z-score tolerance bands.

Table 4: ~~RMSE and R2 value of sensitivity runs~~Inputs to test for the effect of randomness ~~of~~ in the model

Varied Parameter	Run 1 (Base Case)	Run 2	Run 3	Run 4	Run 5	Run 6 (Final Model)
Scaling	N	Y (0,1)~~Y(0,1)~~	Y (-1,1)~~Y(0,1)~~	Y (-1,1)~~Y(-1,1)~~	Y (-1,1)~~Y(-1,1)~~	Y (-1,1)
VW DH Sensor	NA	Z01~~Z09~~	Z05~~Z01~~	Z05~~Z05~~	Z01~~Z05~~	Z05
Injection WHP Sensor	NA	Y~~Y~~	Y~~Y~~	N~~Y~~	Y~~N~~	Y
Temp Sensor	NA	N~~N~~	N~~N~~	Y~~N~~	Y~~Y~~	Y
Z-Score ~~Inj_Diff~~Tolerance	NA	25~~20~~	25~~25~~	25~~25~~	25~~25~~	25
~~VW Zero Values~~	~~NA~~	~~Yes~~	~~No~~	~~No~~	~~No~~	~~No~~
~~Test RMSE~~	~~5.54~~	~~2.65~~	~~1.82~~	~~1.98~~	~~1.50~~	~~1.31~~
~~Val RMSE~~	~~NA~~	~~1.75~~	~~2.20~~	~~1.90~~	~~2.01~~	~~1.73~~
~~Val R2~~	~~NA~~	~~0.73~~	~~0.63~~	~~0.72~~	~~0.69~~	~~0.77~~

Formatted: Justified

Table 5: RMSE and R2 output values to determine if the model is accurately able to account for randomness

Parameter	Run 1 (Base Case)	Run 2	Run 3	Run 4	Run 5	Run 6 (Final Model)
Test RMSE	5.54	1.82~~2.65~~	1.98~~1.82~~	1.50~~1.98~~	~~1.50~~ 1.48	1.49~~1.31~~
Val RMSE	NA	2.20~~1.75~~	1.90~~2.20~~	2.01~~1.90~~	~~2.01~~ 1.71	~~1.73~~1.49
Val R2	NA	0.63~~0.73~~	0.72~~0.63~~	0.69~~0.72~~	~~0.69~~ 0.78	0.83~~77~~

Formatted Table

Randomness

NN themselves are not inherently stochastic, as they follow deterministic mathematical operations, and the inputs, weights, and biases are all fixed values during inference. However, the stochastic nature of the NN model becomes apparent when seed values are varied; different seed values result in different results.

Our next test for the generality of the model involved running various seed values (we utilised 10 different values) and determining if both high and low amplitude delta values could be predicted. ~~Six~~ Seven selected results are displayed in Table 6 while Figure 7 to show the range of comparison with respect to the first unseeded run.

We observe that while all runs can predict the anomalies, the signature of the minor differences varies between seed values (Table 6). We also observe that the RMSE and R2 values on the validation set all lie within a small range (±10% or up to 0.2 psi absolute) of the unseeded value (Figure 7). Thus, to account for randomness and to retain the unbiased nature of the model, an unseeded model is selected for deployment.

Table 6: RMSE and R2 value of sensitivity runs to test randomness of model

Variables	Run 1 (Base Case)	Run 2	Run 3	Run 4	Run 5	Run 6	Run 7
Seed Value (SV)	Unseeded	2250	42	2023	1	111	88~~111~~
Val RMSE	1.79~~3~~	1.55	1.69	1.69	1.64	1.87	1.70~~1.87~~
Val R2	~~0.77~~0.83	0.82	0.78	0.78	0.79	0.73	0.78~~0.73~~

Formatted Table

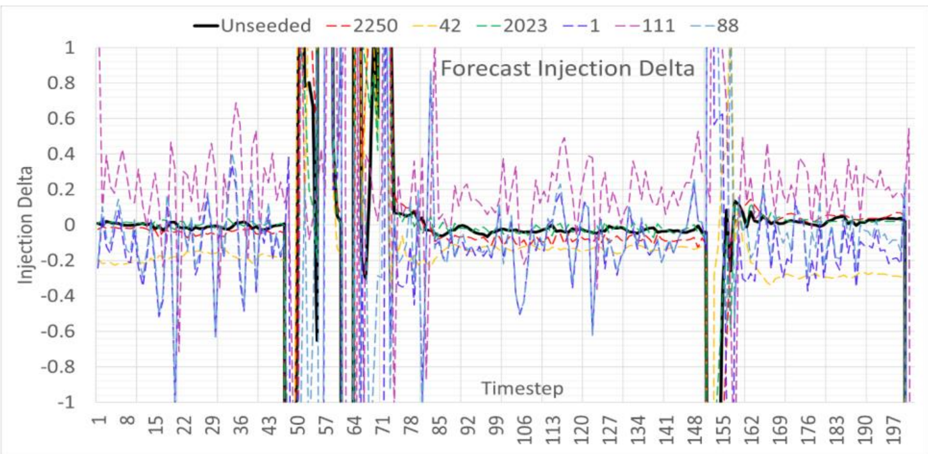


Figure 7: Injection Delta forecasts of sensitivity run to test randomness of model – all results show small perturbations around the unseeded value

Evaluation against the "Hold-out" Data

We test the predictive capability of the model by passing downhole sensor measurements never seen by the model (our "hold out" data set), to determine if the model can detect injection rate anomalies.

Figure 8 shows the results of this test, where our model has successfully predicated the presence of four anomalies in the injection rates. When we plot this prediction against what the actual injection rates were (our "ground truth" data), we observe a near perfect overlap in results.

~~shows the model inputs and prediction on the "hold-out" dataset. The result shows that there are four anomalies in the predicted injection deltas.~~

~~When correlated back to the input dataset, w~~We observe that for the negative injection deltas, there are corresponding decreases in injection pressure implying a decreased CO_2 injection rate.

The prediction data also shows corresponding increase in injection pressure during positive injection deltas, implying an increased injection rate. Corresponding changes can also be seen on the other inputs such as temperature and CO_2 vent rate.

The fact that our model can predict these anomalies using measured sensor data is encouraging; as an operator who is interpreting this result, it would be prudent to firstly ask if these injection deltas are expected. If they are not, then it behoves the operator to investigate/ monitor the well to determine what sort of remedial action should be taken.

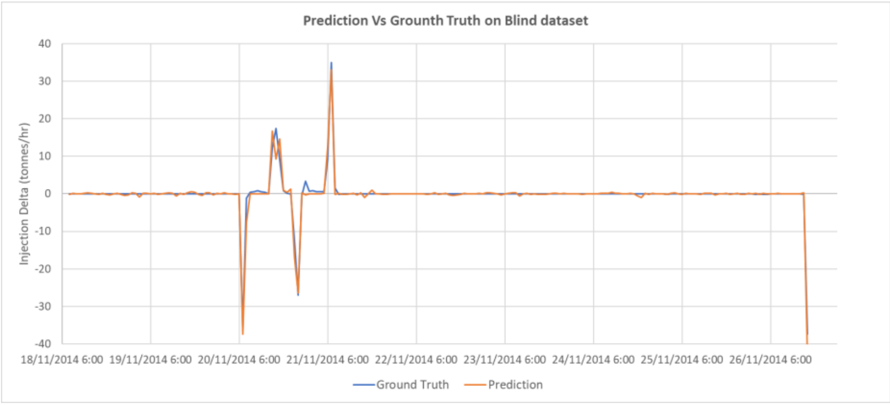


Figure 8: Input (blue line) and prediction (red line) on blind "hold out" dataset

Discussion & Recommendations

We think there are several ways to further enhance the model's performance. First, incorporating the response of the operator when an anomaly is marked as safe reduces the likelihood of flagging similar anomalies in the future. This feedback loop mechanism can help refine the model's predictive accuracy and ensure more reliable results over time.

Secondly, exploring alternative methods for outlier removal, and implementing advanced techniques to identify and handle outliers effectively will improve the model's ability to identify genuine anomalies, while minimizing false positives.

Thirdly, the workflow of the model can be improved to reduce runtime. This optimization involves running multiple sets of model ensembles, and aggregating their outputs to obtain a more "generalised" model. Generalising the model can further enhance performance and provide more reliability when it comes to anomaly detection.

Lastly, we also think the results of the model need integration with other monitoring technology; 4D seismic monitoring, tiltmeters, downhole sensors, tracers deployed and geochemical monitoring are just some examples of other data sets that should be incorporated.

Formatted: Indent: First line: 0.2"

Formatted: Indent: First line: 0"

Conclusion

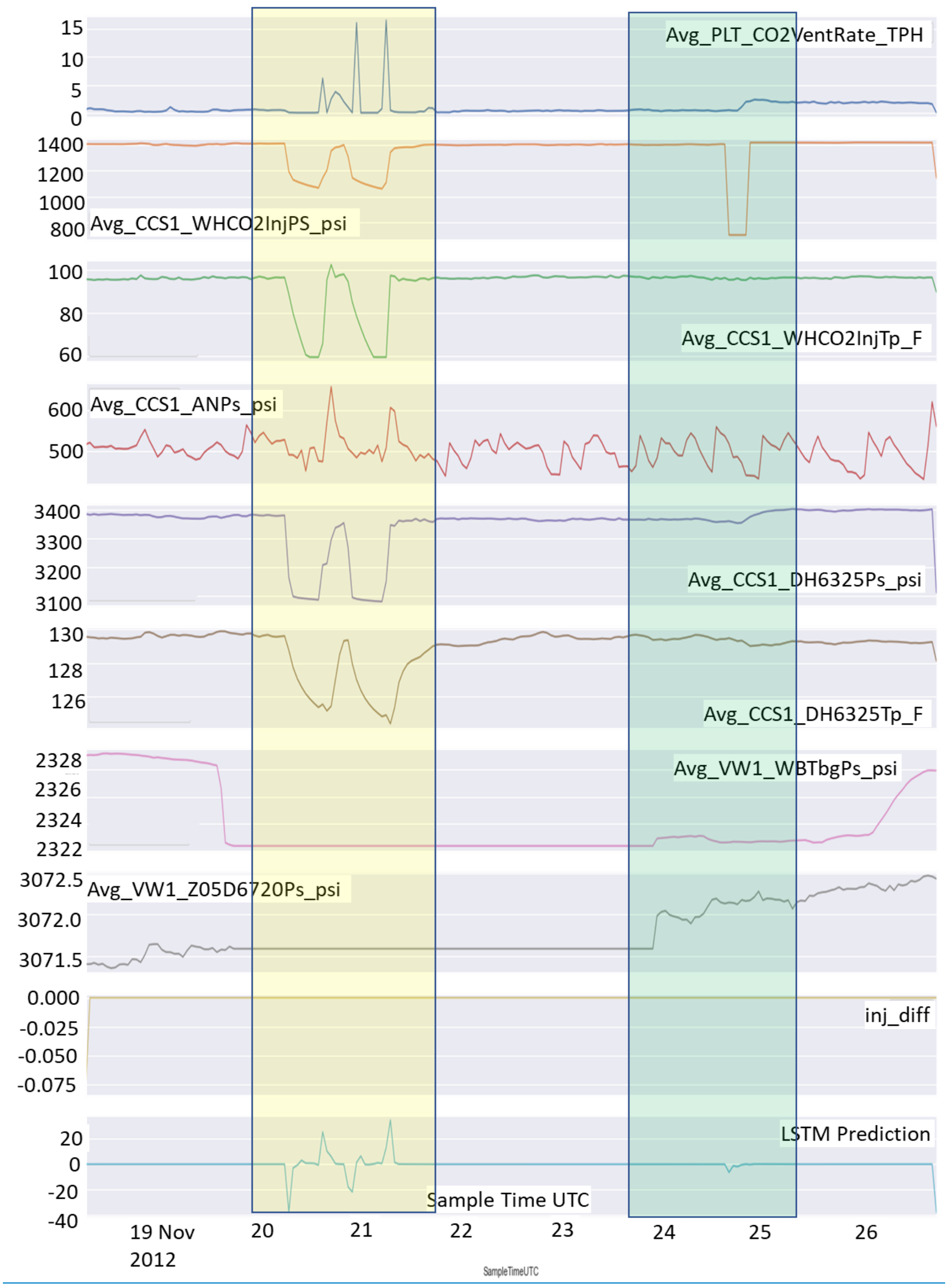
The IBDP project involved injection of ~1000 tonnes/day of CO_2 into a single well, for a three year, resulting in ~995, 215 cumulative tonnes of CO_2 being injected. In view of the growing importance of CCUS in achieving climate targets, we believe the wealth of open-source time-series data from this project can be applied to derisk CCUS monitoring.

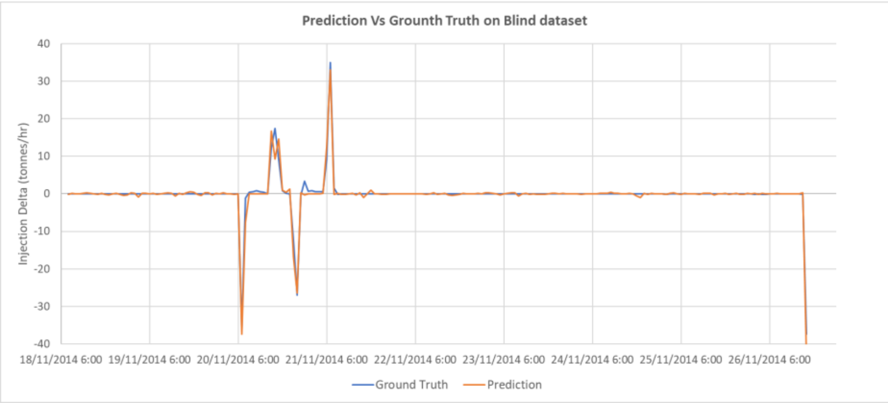
In this work, we demonstrated how an LSTM based machine learning model has been developed and implemented to predict injection deltas of active CO_2 injection. We demonstrate that our predicted models do well based on RMSE and R2 scores against both the training and validation data sets. Our model was able to predict both large and small anomalies, and we demonstrated that the model is sufficiently generalised for this single input data source.

The model can detect anomalies which operators can use when determining which wells to inspect for potential leaks, especially in scenarios where multiple wells are used for injection. By passing the measured data through the model, one can determine at which well~~containment breach~~ location downhole losses were observed during the injection process. The model can also help engineers to perform computational based de-risking of geological formations, by understanding how changing certain storage parameters impacts CO_2 containment. The model will also aid in the understanding of the injection process and optimising well operations and costs, reducing the reliance on periodic (or ad-hoc depending on operator budget) tests like well annulus pressures, casing tests, and use of cased hole reservoir saturation tools.

~~The primary objective of this model is to detect anomalies and alert operators to closely inspect the wells for potential leaks. This predictive capability becomes especially valuable in scenarios where multiple wells are in operation, as it eliminates the need for additional operators, thereby reducing operational costs.~~ We also recommended a series of improvements and model enhancements in this paper which would increase the machine learning model's predictive ability, potentially providing operators with timely alerts for potential leaks while optimizing operational efficiency and cost-effectiveness.

Formatted: Indent: First line: 0"


Avg_PLT_CO2VentRate_TPH
Avg_CCS1_WHCO2InjPS_psi
Avg_CCS1_WHCO2InjTp_F
Avg_CCS1_ANPs_psi
Avg_CCS1_DH6325Ps_psi
Avg_CCS1_DH6325Tp_F
Avg_VW1_WBTbgPs_psi
Avg_VW1_Z05D6720Ps_psi
inj_diff
LSTM Prediction
Sample Time UTC
19 Nov
2012
20
21
22
23
24
25
26
SampleTimeUTC



~~Figure 8: Input and prediction on "hold out" dataset~~

Formatted: Centered

<u>Nomenclature</u>

Formatted Table

GHG	greenhouse gas
CO_2	carbon dioxide
CH_4	methane
N_2O	nitrous oxide
EPA	Environmental Protection Agency
CCUS	Carbon Capture Utilisation and Storage
EOR	Enhanced Oil Recovery
Δ	injection rates deltas
IR	injection rate
ML	machine learning
ARIMA	Autoregressive Integrated Moving Average
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARCH/GARCH	Autoregressive Conditional Heteroskedasticity/ Generalized Autoregressive Conditional Heteroskedasticity

DCA	decline curve analysis
q_i	initial rate (bbls/day)
D_i	initial decline rate (units)
b	degree of curvature of the line
AI	artificial intelligence
LSTM	Long Short-Term Memory
IBDP	Illinois Basin - -Decatur Project
TD	total depth
MAD	median absolute deviation
NN	neural networks
MAE	mean absolute error
MSE	mean squared error
RMSE	root mean squared error
R^2	coefficient of determination
lr	Learning Rate
ADAM	Adaptive Moment Estimation
Z score	a statistical measurement describing a value to the mean of a group of values
CCS1_ANPs_psig	CCS1 annulus pressure in psi
CCS1_DHPs_psig	CCS1 downhole pressure in psi
CCS1_DHTp_F	CCS1 downhole temperature in Deg F
CCS1_WHCO2InjPs_psi	CCS1 wellhead pressure in psi
CCS1_WHCO2InjTp_F	CCS1 wellhead temperature in Deg F
PLT_CO2InjRate_TPH	CO2 injection rate in tonnes per hour
PLT_CO2VentRate_TPH	CO2 vent rate in tonnes per hour
VW1_ANPs_psig	Validation well (VW1) annulus pressure in psi
VW1_PTbgPs_psig	VW1 tubing pressure in psi

Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt
Formatted: Font: (Default) Times New Roman, 12 pt

VW1_PTbgTp_F	VW1 tubing temperature in Deg F
VW1_Z01D7061Ps_psi	VW1 Zone01 pressure (7061 ft) in psi
VW1_Z01D7061Tp_F	VW1 Zone01 temperature (7061 ft) in Deg F
VW1_Z02D6982Ps_psi	VW1 Zone02 pressure (6982 ft) in psi
VW1_Z02D6982Tp_F	VW1 Zone02 temperature (6982 ft) in Deg F
VW1_Z03D6945Ps_psi	VW1 Zone03 pressure (6945 ft) in psi
VW1_Z03D6945Tp_F	VW1 Zone03 temperature (6945 ft) in Deg F
VW1_Z04D6837Ps_psi	VW1 Zone04 pressure (6837 ft) in psi
VW1_Z04D6837Tp_F	VW1 Zone04 temperature (6837 ft) in Deg F
VW1_Z05D6720Ps_psi	VW1 Zone05 pressure (6720 ft) in psi
VW1_Z05D6720Tp_F	VW1 Zone05 temperature (6720 ft) in Deg F
VW1_Z06D6632Ps_psi	VW1 Zone06 pressure (6632 ft) in psi
VW1_Z06D6632Tp_F	VW1 Zone06 temperature (6632 ft) in Deg F
VW1_Z07D6416Ps_psi	VW1 Zone07 pressure (6416 ft) in psi
VW1_Z07D6416Tp_F	VW1 Zone07 temperature (6416 ft) in Deg F
VW1_Z08D5840Ps_psi	VW1 Zone08 pressure (5840 ft) in psi
VW1_Z08D5840Tp_F	VW1 Zone08 temperature (5840 ft) in Deg F
VW1_Z0910D5482Ps_psi	VW1 Zone0910 pressure (5482 ft) in psi
VW1_Z0910D5482Tp_F	VW1 Zone0910 temperature (5482 ft) in Deg F
VW1_Z09D5653Ps_psi	VW1 Zone09 pressure (5653 ft) in psi
VW1_Z09D5653Tp_F	VW1 Zone09 temperature (5653 ft) in Deg F
VW1_Z10D5001Ps_psi	VW1 Zone10 pressure (5001 ft) in psi
VW1_Z10D5001Tp_F	VW1 Zone10 temperature (5001 ft) in Deg F
VW1_Z11D4917Ps_psi	VW1 Zone11 pressure (4917 ft) in psi
VW1_Z11D4917Tp_F	VW1 Zone11 temperature (4917 ft) in Deg F
inj_diff	difference in the injection rate (IR) at time t and time (t-1) in psi

Acknowledgements

The authors wish to acknowledge Ryan Lazaroo for peer review of this work.

Reference

[1] T. Nakazawa , “Current understanding of the global cycling of carbon dioxide, methane, and nitrous oxide.,” *Proceedings of the Japn Academy, Series B Physical and Biological Sciences,* vol. 96, no. 9, pp. 394-419, 2020.

[2] Z. Liu, Z. Deng, S. Davis and P. Ciais, “Monitoring global carbon emissions in 2022,” *Nature reviews earth and enviroment,* vol. 4, pp. 205-206, 2023.

[3] R. A. Bauer, R. E. Will, S. Greenberg and S. G. Whittaker, “Illinois Basin – Decatur project.,” in *Geophysics and Geosequestration*, Cambridge University Press, 2019, pp. 339-370.

[4] T. A. Torp and J. Gale, “Demonstrating storage of CO2 in geological reservoirs: The Sleipner and SACS projects.,” *Energy* , vol. 29.9, no. 10, pp. 1361-1369, 2004.

[5] P. S. Ringrose, A. S. Mathieson, I. W. Wright, F. Selama, O. Hansen, R. Bissell, N. Saoula and J. Midgley, “The In Salah CO2 Storage Project: Lessons Learned and Knowledge Transfer,” *Energy Procedia,* vol. 37, pp. 6226-6236, 2013.

[6] J. G. D. Gooijer and R. J. Hyndman, “25 years of time series forecasting,” *International Journal of Forecasting,* vol. 22, no. 3, pp. 443-473, 2006.

[7] E. S. Gardner, “Exponential smoothing: The state of the art,” *Journal of Forecasting,* vol. 4, no. 1, pp. 1-28, 1985.

[8] R. D. Snyder, “Recursive Estimation of Dynamic Linear Models,” *Journal of the Royal Statistical Society. Series B (Methodological),* vol. 47, no. 2, p. 272–276, 1985.

[9] R. H. Scumway and D. S. Stoffer, Time Series Regression and ARIMA Models, New York: Springer, 2000.

[10] G. Huyot, K. Chiu, J. Higginson and N. Gait, “Analysis of Revisions in the Seasonal Adjustment of Data Using X-11-Arima Model-Based filters,” *International Journal of Forecasting*, vol. 2, no. 2, pp. 217-229, 1986.

[11] S. H. Babbs and K. B. Nowman, “Kalman filtering of generalized Vasicek term structure models,” *Journal of financial and quantitative analysis*, vol. 34, no. 1, pp. 115-130, 1999.

[12] M. P. Clements, P. H. Franses and N. R. Swanson, “Forecasting economic and financial time-series with non-linear models,” *International journal of forecasting*, vol. 20, no. 2, pp. 169-183, 2004.

[13] B. K. Ray, “Long-range forecasting of IBM product revenues using a seasonal fractionally differenced ARMA model,” *International Journal of Forecasting*, vol. 9, no. 2, pp. 255-269, 1993.

[14] S. J. Taylor, “Forecasting the volatility of currency exchange rates,” *International Journal of Forecasting*, vol. 3, no. 1, pp. 159-170, 1987.

[15] T. R. Willemain, C. N. Smart, J. H. Shockor and P. A. DeSautels, “Forecasting intermittent demand in manufacturing: a comparative evaluation of Croston's method,” *International Journal of Forecasting*, vol. 10, no. 4, pp. 529-538, 1994.

[16] J. J. Arps, “Analysis of Decline Curves,” *Transactions of the AIME*, Vols. SPE-945228-G, no. 160, p. 228–247, 1945.

[17] M. J. Fetkovich, E. J. Fetkovich and M. D. Fetkovich, “Useful Concepts for Decline-Curve Forecasting, Reserve Estimation, and Analysis,” *SPE Res Eng*, vol. 11, no. 1, p. 13–22, 1996.

[18] A. Clark, L. Lake and T. Patzek, “Production Forecasting with Logistic Growth Models,” in *SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA, 2011.

[19] A. Duong, “An Unconventional Rate Decline Approach for Tight and Fracture-Dominated Gas Wells,” in *Canadian Unconventional Resources and International Petroleum Conference.* , Calgary, Alberta, Canada, 2010.

[20] D. Ilk, J. A. Rushing, A. D. Perego and T. A. Blasingame, “Exponential vs. Hyperbolic Decline in Tight Gas Sands — Understanding the Origin and Implications for Reserve Estimates Using Arps' Decline Curves.,” in *Paper presented at the SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA, 2008.

[21] P. Valko, “Assigning value to stimulation in the Barnett Shale: a simultaneous analysis of 7000 plus production hystories and well completion records,” in *SPE Hydraulic Fracturing Technology Conference* , Woodlands, Texas. , 2009.

[22] M. Kumar, K. Swaminathan , A. Rusli and A. Thomas-Hy, “Applying Data Analytics & Machine Learning Methods for Recovery Factor Prediction and Uncertainty Modelling,” *SPE Asia Pacific Oil & Gas Conference and Exhibition*, Vols. SPE-210769-MS , pp. 1-12, 2022.

[23] N. Ibrahim, A. Alharbi, T. Alzahrani, A. Abdulkarim, I. Alessa, A. Hameed, A. Albabtain, D. Alqahtani, M. Alsawwaf and A. Almuqhim, “Well Performance Classification and Prediction: Deep Learning and Machine Learning Long Term Regression Experiments on Oil, Gas, and Water Production,” *Sensors*, vol. 22, no. 5326, pp. 1-22, 2022.

[24] P. Panja, W. Jia and B. Mcpherson, “Prediction of well performance in SACROC field using stacked Long Short-Term Memory (LSTM) network,” *Expert Systems With Applications* , vol. 205, no. 117670, pp. 1-25, 2022.

[25] Y. Dong, Y. Zhang and X. Cheng, “Reservoir Production Prediction Model Based on a Stacked LSTM Network and Transfer Learning,” *ACS Omega*, vol. 6, pp. 34700-34711, 2021.

[26] P. Yao, Z. Yu, Y. Zhang and T. Xu, “Application of machine learning in carbon capture and storage: An in-depth insight from the perspective of geoscience,” *Fuel*, vol. 333, no. 1, p. 126296, 2023.

[27] B. Chen, D. R. Harp, Y. Lin, E. H. Keating and R. J. Pawar, “Geologic CO2 sequestration monitoring design: A machine learning and uncertainty quantification based approach,” *Applied Energy*, vol. 225, no. 1, pp. 332-345, 2018.

[28] J. You, W. Ampomah, Q. Sun, E. J. Kutsienyo, R. S. Balch, Z. Dai, M. Cather and X. Zhang, "Machine learning based co-optimization of carbon dioxide sequestration and oil recovery in CO2-EOR project," *Journal of Cleaner Production*, vol. 260, p. 120866, 2020.

[29] U. P. Iskander and M. Kurihara, "Long Short-term Memory (LSTM) Networks for Forecasting Reservoir Performances in Carbon Capture, Utilisation, and Storage (CCUS) Operations," *Scientific Contributions Oil & Gas*, vol. 45, no. 1, pp. 35 - 50, 2022.

[30] M. Alsharif, M. Younes and J. Kim, "Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation: The Case Study of Seoul, South Korea.," *Symmetry*, vol. 11, no. 2, p. 240, 2019.

[31] S. Siami-Namini, N. Tavakoli and A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series," *17th IEEE international conference on machine learning and applications (ICMLA)*, pp. 1394-1401, 2018.

[32] S. A. Ludwig, "Comparison of time series approaches applied to greenhouse gas analysis: ANFIS, RNN, and LSTM.," *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pp. 1-6, 2019.

[33] Y. Ning, H. Kazemi and P. Tahmasebi, "A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet," *Computers & Geosciences*, vol. 164, no. 105126, 2022.

[34] A. Parasyris, G. Alexandrakis and G. Kozyrakis, "Predicting Meteorological Variables on Local Level with SARIMA, LSTM and Hybrid Techniques," *Atmosphere*, vol. 13, no. 878, 2022.

[35] K. Greff, K. Srivastava, J. Koutnik, B. R. Steunebrink and J. Schmidhuber, "LSTM: A Search Space Odyssey," *Transactions on Neural Networks and Learning Systems*, vol. 28, no. 10, pp. 2222-2232, 2016.

[36] G. Reikard, "Predicting solar radiation at high resolutions: A comparison of time series forecasts," *Solar Energy*, vol. 83, no. 3, p. 342–349, 2009.

~~[1] T. Nakazawa , "Current understanding of the global cycling of carbon dioxide, methane, and nitrous oxide.," *Proceedings of the Japn Academy, Series B Physical and Biological Sciences*, vol. 96, no. 9, pp. 394-419, 2020.~~

~~[2] Z. Liu, Z. Deng, S. Davis and P. Ciais, "Monitoring global carbon emissions in 2022," *Nature reviews earth and enviroment*, vol. 4, pp. 205-206, 2023.~~

~~[3] R. A. Bauer, R. E. Will, S. Greenberg and S. G. Whittaker, "Illinois Basin – Decatur project.," in *Geophysics and Geosequestration*, Cambridge University Press, 2019, pp. 339-370.~~

~~[4] T. A. Torp and J. Gale, "Demonstrating storage of CO2 in geological reservoirs: The Sleipner and SACS projects.," *Energy* , vol. 29.9, no. 10, pp. 1361-1369, 2004.~~

~~[5] P. S. Ringrose, A. S. Mathieson, I. W. Wright, F. Selama, O. Hansen, R. Bissell, N. Saoula and J. Midgley, "The In Salah CO2 Storage Project: Lessons Learned and Knowledge Transfer," *Energy Procedia*, vol. 37, pp. 6226-6236, 2013.~~

~~[6] J. G. D. Gooijer and R. J. Hyndman, "25 years of time series forecasting," *International Journal of Forecasting*, vol. 22, no. 3, pp. 443-473, 2006.~~

~~[7] E. S. Gardner, "Exponential smoothing: The state of the art," *Journal of Forecasting*, vol. 4, no. 1, pp. 1-28, 1985.~~

~~[8] R. D. Snyder, "Recursive Estimation of Dynamic Linear Models," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 47, no. 2, p. 272–276, 1985.~~

~~[9] R. H. Scumway and D. S. Stoffer, Time Series Regression and ARIMA Models, New York: Springer, 2000.~~

~~[10] G. Huyot, K. Chiu, J. Higginson and N. Gait, "Analysis of Revisions in the Seasonal Adjustment of Data Using X-11-Arima Model-Based filters," *International Journal of Forecasting*, vol. 2, no. 2, pp. 217-229, 1986.~~

~~[11] S. H. Babbs and K. B. Nowman, "Kalman filtering of generalized Vasicek term structure models," *Journal of financial and quantitative analysis*, vol. 34, no. 1, pp. 115-130, 1999.~~

~~[12] M. P. F. P. H. &. S. N. R. Clements, "Forecasting economic and financial time series with non-linear models," *International journal of forecasting*, vol. 20, no. 2, pp. 169-183, 2004.~~

~~[13] B. K. Ray, "Long-range forecasting of IBM product revenues using a seasonal fractionally differenced ARMA model," *International Journal of Forecasting*, vol. 9, no. 2, pp. 255-269, 1993.~~

~~[14] S. J. Taylor, "Forecasting the volatility of currency exchange rates," *International Journal of Forecasting*, vol. 3, no. 1, pp. 159-170, 1987.~~

~~[15] T. R. Willemain, C. N. Smart, J. H. Shockor and P. A. DeSautels, "Forecasting intermittent demand in manufacturing: a comparative evaluation of Croston's method," *International Journal of Forecasting*, vol. 10, no. 4, pp. 529-538, 1994.~~

~~[16] J. J. Arps, "Analysis of Decline Curves," *Transactions of the AIME*, Vols. SPE-945228-G, no. 160, p. 228–247, 1945.~~

~~[17] A. L. L. a. T. P. Clark, "Production Forecasting with Logistic Growth Models," in *SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA, 2011.~~

~~[18] A. Duong, "An Unconventional Rate Decline Approach for Tight and Fracture-Dominated Gas Wells," in *Canadian Unconventional Resources and International Petroleum Conference.* , Calgary, Alberta, Canada, 2010.~~

~~[19] D. R. J. A. P. A. D. a. T. A. B. Ilk, "Exponential vs. Hyperbolic Decline in Tight Gas Sands — Understanding the Origin and Implications for Reserve Estimates Using Arps' Decline Curves.," in *Paper presented at the SPE Annual Technical Conference and Exhibition*, Denver, Colorado, USA, 2008.~~

~~[20] P. Valko, "Assigning value to stimulation in the Barnett Shale: a simultaneous analysis of 7000 plus production hystories and well completion records," in *SPE Hydraulic Fracturing Technology Conference* , Woodlands, Texas. , 2009.~~

~~[21] M. Kumar, K. Swaminathan , A. Rusli and A. Thomas Hy, "Applying Data Analytics & Machine Learning Methods for Recovery Factor Prediction and Uncertainty Modelling," *SPE Asia Pacific Oil & Gas Conference and Exhibition,* Vols. SPE-210769-MS , pp. 1-12, 2022.~~

~~[22] N. Ibrahim, A. Alharbi, T. Alzahrani, A. Abdulkarim, I. Alessa, A. Hameed, A. Albabtain, D. Alqahtani, M. Alsawwaf and A. Almuqhim, "Well Performance Classification and Prediction: Deep Learning and Machine Learning Long Term Regression Experiments on Oil, Gas, and Water Production," *Sensors,* vol. 22, no. 5326, pp. 1-22, 2022.~~

~~[23] P. Panja, W. Jia and B. Mcpherson, "Prediction of well performance in SACROC field using stacked Long Short-Term Memory (LSTM) network," *Expert Systems With Applications* , vol. 205, no. 117670, pp. 1-25, 2022.~~

~~[24] Y. Dong, Y. Zhang and X. Cheng, "Reservoir Production Prediction Model Based on a Stacked LSTM Network and Transfer Learning," *ACS Omega,* vol. 6, pp. 34700-34711, 2021.~~

~~[25] P. Yao, Z. Yu, Y. Zhang and T. Xu, "Application of machine learning in carbon capture and storage: An in-depth insight from the perspective of geoscience," *Fuel,* vol. 333, no. 1, p. 126296, 2023.~~

~~[26] B. Chen, D. R. Harp, Y. Lin, E. H. Keating and R. J. Pawar, "Geologic CO2 sequestration monitoring design: A machine learning and uncertainty quantification based approach," *Applied Energy,* vol. 225, no. 1, pp. 332-345, 2018.~~

~~[27] J. You, W. Ampomah, Q. Sun, E. J. Kutsienyo, R. S. Balch, Z. Dai, M. Cather and X. Zhang, "Machine learning based co-optimization of carbon dioxide sequestration and oil recovery in CO2-EOR project," *Journal of Cleaner Production,* vol. 260, p. 120866, 2020.~~

~~[28] U. P. Iskander and M. Kurihara, "Long Short-term Memory (LSTM) Networks for Forecasting Reservoir Performances in Carbon Capture, Utilisation, and Storage (CCUS) Operations," *Scientific Contributions Oil & Gas,* vol. 45, no. 1, pp. 35 – 50, 2022.~~

~~[29] M. Alsharif, M. Younes and J. Kim, "Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation: The Case Study of Seoul, South Korea.," *Symmetry*, vol. 11, no. 2, p. 240, 2019.~~

~~[30] S. Siami-Namini, N. Tavakoli and A. S. Namin, "A comparison of ARIMA and LSTM in forecasting time series," *17th IEEE international conference on machine learning and applications (ICMLA)*, pp. 1394-1401, 2018.~~

~~[31] S. A. Ludwig, "Comparison of time series approaches applied to greenhouse gas analysis: ANFIS, RNN, and LSTM.," *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pp. 1-6, 2019.~~

~~[32] Y. Ning, H. Kazemi and P. Tahmasebi, "A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet," *Computers & Geosciences*, vol. 164, no. 105126, 2022.~~

~~[33] A. Parasyris, G. Alexandrakis and G. Kozyrakis, "Predicting Meteorological Variables on Local Level with SARIMA, LSTM and Hybrid Techniques," *Atmosphere*, vol. 13, no. 878, 2022.~~

~~[34] K. Greff, K. Srivastava, J. Koutnik, B. R. Steunebrink and J. Schmidhuber, "LSTM: A Search Space Odyssey," *Transactions on Neural Networks and Learning Systems*, vol. 28, no. 10, pp. 2222-2232, 2016.~~

~~[35] G. Reikard, "Predicting solar radiation at high resolutions: A comparison of time series forecasts," *Solar Energy*, vol. 83, no. 3, p. 342–349, 2009.~~

Declaration of interests

☒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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Munish Kumar:

Conceptualization, Methodology, Software, Data Curation, Formal analysis, Writing - Review & Editing, Supervision, Project administration

Kannappan Swaminathan:

Software, Formal analysis, Formal analysis, Writing – Editing, Resources, Data Curation, Writing - Original Draft, Visualization