A Multiscale Recurrent Neural Network Model for Long-Term Prediction of Geothermal Energy Production

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ABSTRACT
Management and optimization of energy recovery from geothermal reservoirs rely on accurate prediction of energy production performance for alternative development scenarios. While physics-based reservoir simulation models are traditionally used as a comprehensive approach to predict the response of geothermal reservoirs to different production strategies, data-driven models can serve as efficient fit-for-purpose tools for rapid evaluation and screening of alternative production and development plans as well as for facilitating daily operation and surveillance decisions. We evaluate the use of recurrent neural networks (RNN), as machine learning architectures for representation and prediction of sequential/dynamic data, for long-term prediction of geothermal energy production. As a universal approximator that can capture complex and nonlinear trends in data, RNN has enjoyed great success in many applications. Since RNN primarily exploits statistical relations in training data to generate predictions, it can be challenged in applications where extrapolation beyond the training data range is needed. We explore new RNN architectures and training approaches to improve its generalization power for long-term prediction of geothermal reservoir performance. Since historical monitoring and performance observations in geothermal fields contain short-term and long-term patterns, we develop multiscale RNN architectures and the corresponding training implementations to learn both short-term and long-term trends in the data and use them for future predictions. We present the developed architecture and training process and show its application to simulated datasets from a field-scale model.

1. INTRODUCTION
The availability of models that can accurately predict flow responses under different scenarios is important for the development of geothermal energy. Physics-based models provide comprehensive predictions by simulating the complex physical processes in the reservoir. Along with physics-based models, data-driven models have been applied to geothermal applications. In contrast to physics-based models that have complex model development workflows and extensive computational demand to run them, data-driven models are relatively easy to build and, once trained, extremely fast to run. The computational advantage of data-driven models makes them efficient alternatives to physics-based models, especially when used in computationally intensive workflows such as optimization and uncertainty quantification.

Recurrent neural network (RNN) is a class of neural networks, in which a sequence of repeated neurons maps the sequential input data to the predictions. RNN is well-known for capturing the dynamics in data sequences and has been applied in geothermal predictions. Gudmundsdottir et al. (2020) illustrate the use of RNN for tracer concentration prediction. Gangwani et al. (2020) apply long short-term memory (LSTM) sequence-to-sequence architecture to the production prediction. Jiang et al. (2021) combine RNN with a labeling scheme to predict brine temperature from production wells while accounting for shut-in periods. Liu et al. (2021) designed a dynamic neural network architecture for performance prediction and fault detection in geothermal operations. Most of these studies focus on problems in which the system is stationary, and the predictions are short-term and close to the observed time steps (the first quadrant in Figure 1). Studies have also shown that RNN works for problems where there are additional simulation realizations despite the data patterns not being persistent (the fourth quadrant in Figure 1).

Neural networks have shown superior performance in many challenging applications. Despite their great success in recent years, one of the major drawbacks of neural networks is their weak extrapolation ability, which is due to their nonlinear nature. Interpolation is defined as predicting at a position in-between data points, while extrapolation is defined as predicting beyond the existing (training) data points (Kolmogoroff et al., 1941; Wiener et al., 1949). Figure 2 shows the difficulty in extrapolating beyond the training data (the vertical dashed line) in a simple synthetic example, illustrating why neural networks are challenged at extrapolating beyond data. All the possible solutions that are shown in Figure 2 match the training data perfectly but provide very different predictions for the testing period. Unless additional information is provided to constrain the predictions, a neural network can provide any of these solutions depending on its trained weights. Another problem that neural networks face in extrapolation with nonstationary data trends is the change in the scale/range of the input (Lai et al., 2018). For example, the data in Figure 2 is monotonically decreasing and is expected to continue to decline during the prediction phase. However, it is likely that the RNN predictions still fall into a range that is similar to those experienced during training.

Multiscale modeling can effectively improve the extrapolation ability of neural networks when the multivariate data contains patterns that can have distinct scales. Lai et al. (2018) designed a long- and short-term model, where an autoregressive model (AR) is responsible for capturing the long-term smooth features, while an RNN model detects and predicts more detailed high-frequency features. The resulting multiscale model shows significant improvement in generalizability beyond the training data. The production enthalpy in geothermal reservoirs tends to exhibit long-term declining patterns that are caused by the pressure loss in the reservoir (and injection of cooler brine) as well as short-term patterns that are caused by the changes in the injection production controls (e.g., flow rate, BHP). The observed
production behavior in geothermal reservoirs motivates the use of multiscale RNN models that consist of a simple model (e.g., fully connected neural network (FCNN)) to describe the long-term trends and a more complex RNN model to capture the local variabilities. The resulting multiscale model is expected to improve the accuracy of long-term predictions in problems that fall into the second quadrant in Figure 1.

This paper presents the developed multiscale RNN model architecture and reports preliminary results by using it in simulated data from a field-scale geothermal reservoir model.

Figure 1: An illustration of the problems defined based on the availability of information and the stationarity of the system. The multiscale RNN model targets the problems with insufficient data, but the patterns are persistent.

Figure 2: A demonstration of the weak extrapolation of neural networks.
2. METHODOLOGY

The details of the multiscale RNN model are introduced in this section.

2.1 RNN Models

RNN is a type of neural network that is formed by a sequence of repeated units that map an input sequence to an output sequence. Each unit in the RNN has a hidden state to store information. By propagating the hidden state through the direction of the sequence, the units have access to historical information. Since the RNN units share the same weights, the RNN sequence can be easily extended to predict data sequences of arbitrary length (future time-steps). RNN models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) implement different gate mechanisms to control the flow of information and propagation of the hidden state. These gate mechanisms introduce additional weights and can increase the complexity and non-uniqueness of the resulting model, thereby affecting the generalizability of RNN when data is limited or when the model is used for extrapolation. The additional nonlinearity from activation functions can also affect the sensitivity of the model to the range of the input data.

2.2 Multiscale RNN Model

Multivariate time series often involve a mixture of long-term and short-term patterns. The different complexity of the patterns could lead to the failure of a single model. This is because complex models that can capture the local nonlinear patterns may face difficulty in simultaneously capturing long-term smooth patterns. Therefore, the generalizability of these models is limited when they are used to predict patterns with multiple scales.

The structure of the proposed multiscale model is shown in Figure 3, in which the RNN model is used to learn short-term nonlinear features, while an overly simple FCNN model is responsible for detecting and predicting long-term smooth features. The RNN component has access to recent historical data as well as the control variables for the prediction steps. On the other hand, the FCNN model only has access to the cumulative controls (coarse-scale information) to prevent it from learning short-term trends. The final prediction is obtained by adding the outputs from the short-term (RNN) and long-term (FCNN) model. To force the two models to detect their intended features, two loss functions are defined for training, short-term loss, and a long-term loss. The long-term loss is the difference between the actual observation and the long-term prediction from the FCNN. Although the short-term loss minimizes the difference between the final prediction and the actual observations, its gradient is only allowed to backpropagate through the short-term model.

![Figure 3: The structure and the training process of the multiscale model](image)

3. NUMERICAL EXPERIMENT

In this section, we will evaluate the accuracy of the proposed model based on data from a calibrated field-scale simulation model. The data is generated using a dual-porosity single-phase numerical model that is built in TETRAD. As shown in Figure 4, there are four fault zones and roughly 35,000 grid blocks in the model. Since there is no connection between the fault zones, we present results for Fault 1 and Fault 2 since they have the simplest and the most complex well configurations.

The dataset consists of 1048 weekly data points, covering about 20 years. The last 434 weeks (approximately eight years) are reserved as the test data, while the other data are used for training. In the model, the wells are controlled by their flow rates, which are changed randomly every two years. The datasets are separated into training sequences that have six time-steps as historical data and the following 52 (one year) time steps as the future. The sequences are chosen to be relatively long to improve the accuracy of the long-term prediction. We train one model for each fault. The models share the same architecture (but have different estimated weights). In testing the long-term
prediction model, all predictions are generated spontaneously at the start without including new observations. To better assess the proposed model, we compare its accuracy to that of regular RNN and regular Autoregressive (AR) models with Exogenous Variables. For the AR models, the control variables (i.e., flow rates) are added as the Exogenous Variables. For the faults that have only one producer, we use Autoregressive with Exogenous Variables (ARX). For the faults with multiple producers, we use Vector Autoregressive with Exogenous Variable (VARX) instead.

Figure 4: The configuration of the simulation model where four faults are present

3.1 Fault Zone 1
We start with Fault Zone 1, which has only one producer and no injector. The normalized flow rate and enthalpy of the producer are shown in Figure 5. The enthalpy is generally smooth, but it also shows signature from the flow rate signal. As mentioned in the methodology section, we also compute the cumulative production, shown in Figure 6, for use in the FCNN model.

Figure 5: The normalized data of Fault Zone 1.
The normalized cumulative flow rate of the producer in Fault Zone 1 is shown in Figure 6.

The enthalpy predictions from the multiscale, RNN, and ARX models are shown in Figure 7. All three models match the training portion of the data fairly well. The prediction from the multiscale RNN model follows the true trend in the data better than the predictions from the other two models. The long-term predictions from RNN and ARX models diverge from the reference case, despite their good matches to the short-term data.

For a statistically meaningful comparison, we repeated this experiment for 10 simulated data realizations, each with a distinct control sequence. For each model, the average mismatch between the true data and predictions over the 10 realizations is shown in Figure 8. The regular RNN model shows the worst performance in both the overall mismatch and the mismatch during the last 52 steps (after eight years). The multiscale RNN model has the lowest overall mismatch, although the mismatch from the ARX model is also not significant. One way to explain the good performance of the ARX model is because the long-term trend in the data is more dominant compared to the short-term changes. Nonetheless, the long-term prediction performance of the multiscale RNN model is superior to that of the ARX model.

Figure 6: The normalized cumulative flow rate of the producer in Fault Zone 1.

Figure 7: The predictions of the enthalpy of the producer in Fault Zone 1 from the multiscale model, RNN, and ARX.

Figure 8: The average mismatch between the predictions and the data of 10 realizations of Fault Zone 1.
3.1 Fault Zone 2
We also applied the models to data from Fault Zone 2, which has a more complex well configuration. There are five injectors and three producers in this fault zone. The normalized data and the cumulative injection and production quantities are shown in Figures 9 and 10, respectively. The enthalpies of the three producers have different features. The enthalpy of Producer 3 shows the strongest signature from the flow rate, while the control signature is barely seen in the enthalpy of Producer 2. The magnitude of the enthalpy change caused by flow rate change gets larger with time.

The enthalpy predictions for each producer are shown in Figure 11. The short-term predictions from all three models are fairly accurate. However, the predictions from the RNN and VARX models show a more significant departure from the true data compared to the predictions from the multiscale model. The average RMSE over 10 repeated experiments with different controls also confirms this observation, as shown in (Figure 12). The multiscale models show a better performance for long-term prediction than the other two models.
Figure 11: The predictions of the enthalpies of the producers in Fault Zone 2 from the multiscale model, RNN, and VARX.

Figure 12: The average mismatches between the predictions and the data of 10 realizations of Fault Zone 2.
4. DISCUSSION AND CONCLUSION

In this paper, we develop a multiscale RNN model for long-term prediction of geothermal reservoirs response for different control strategies. The model utilizes an FCNN with a small number of weights to detect the long-term trends and a more complex RNN model to capture local nonlinear features. Results from the numerical experiments with simulated data suggest that the multiscale RNN provides more accurate predictions than the RNN and AR models, especially when the prediction horizon is long. Comparison between the RNN with and without multiscale structure supports the conclusion that including a multiscale training and prediction mechanism tends to improve the long-term prediction accuracy of the model. The multiscale RNN model also outperforms the AR model, which had a good performance because of the dominantly smooth nature of the data. The proposed model is designed for problems with persistent (stationary) patterns. For nonstationary data, additional information (e.g., physics) may be required to enhance the predictions from data-driven models. Although the multiscale RNN model in this paper has only two models, additional components can be added to the model when the data contains patterns with more than two scales.

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