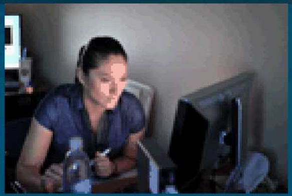
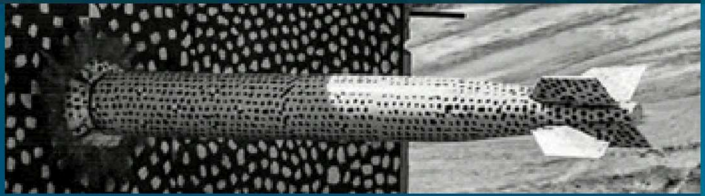
SAND2020-8799PE

Hybrid CNN-LSTM Architecture for Predicting Subsurface Energy Production





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Introduction

1. Shale Reservoirs
2. Horizontal Wells and Hydraulic Fracturing
3. Conventional Modeling Techniques
4. Previous Machine Learning-Based Approaches
5. Proposal

Shale Reservoirs

- Shale source rock became an economically viable and producible hydrocarbon reservoir by 1997
- With respect to the development of shale gas and shale oil assets, horizontal wells that include complex hydraulic fractures have become the norm
- Shale reservoirs are commonly comprised of low permeability rocks that are characterized by a number of unique attributes
- Advances in horizontal drilling and complex hydraulic fracturing has led to a focus on reservoirs, such as Marcellus shale reservoir, that were previously thought un-economical

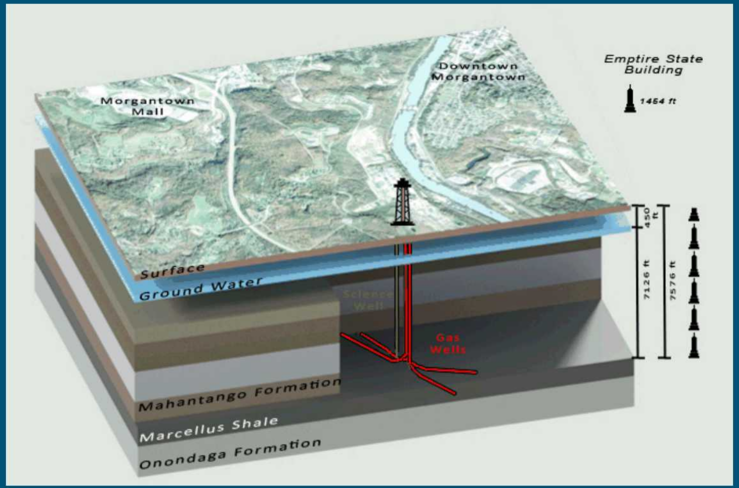

Fig. 1 Block model depicting the science and gas production wells at the Marcellus Shale Energy & Environment Laboratory (MSEEL) [9]

Horizontal Wells and Hydraulic Fracturing

- Horizontal wells are a type of directional drilling technique, dug at angle of at least eighty degrees to a vertical well bore
- Hydraulic fracturing is a widely-used technique for stimulation of oil and gas production from wells drilled in hydrocarbon-bearing formations
- Modeling difficulties arise due to the representation of these processes in the form of fractured, porous media

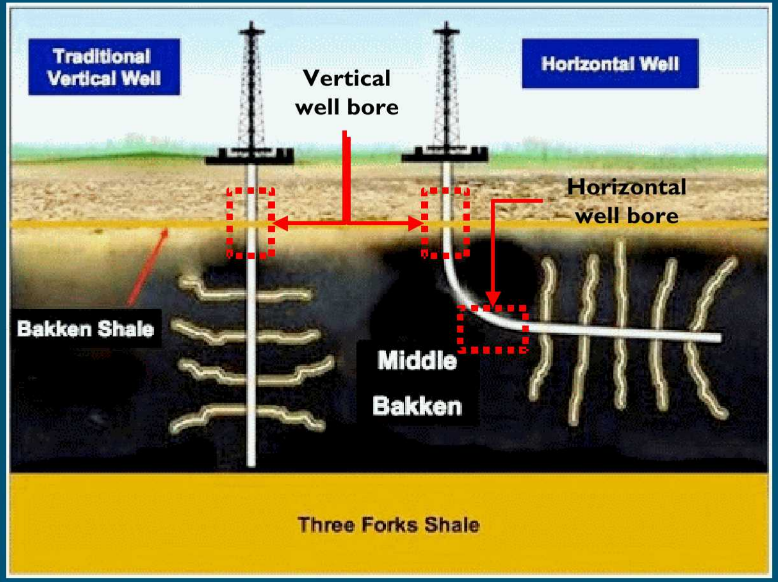

Fig. 2 Comparison of Traditional vertical wells versus Horizontal wells [10]

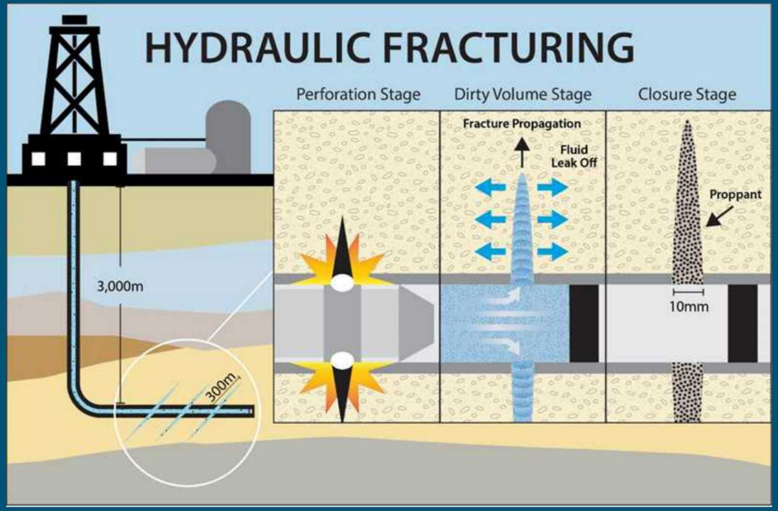

Fig. 3 Diagram of the hydraulic fracturing process [11]

Conventional Modeling Techniques

- Understanding and modeling the complex flow mechanisms, impact of geo-mechanical properties, and design of hydraulic fractures is an open research area
  - Literature has focused on operational and technological challenges of shale oil/gas production
- Conventional reservoir simulation and modeling is a bottom-up approach where a dynamic reservoir model is constructed by augmenting geological model of the reservoir with engineering fluid flow principles [6]
  - Model calibration is performed using the production history in order to obtain the history-matched model
- Reservoir simulation has been a key component towards production optimization. However, there are inherent challenges that must be solved:
  - Developing an understanding of the physics of fluid flow in shale rocks
  - The resource intensive and time-consuming processes associated with reservoir simulation
  - The application of conventional reservoir simulation to shale assets

Previous Machine Learning-based Approaches

- Due to the popularity of shale gas/oil fracturing, an increasing amount of digital field data is being generated and collected [5]
- Approaches focus on 'hard data' instead of rigid representations of flow and transport mechanisms in shale reservoirs
- Development of an AI-based framework that utilizes both field measurements and measured fracturing variables [4]
  - Utilizes a data-driven technique know as Top-Down modeling to take into account all aspects of shale production
- Development of a global framework for constructing ML algorithms on digital field data for the purposes of hydraulic fracture design optimization [5]

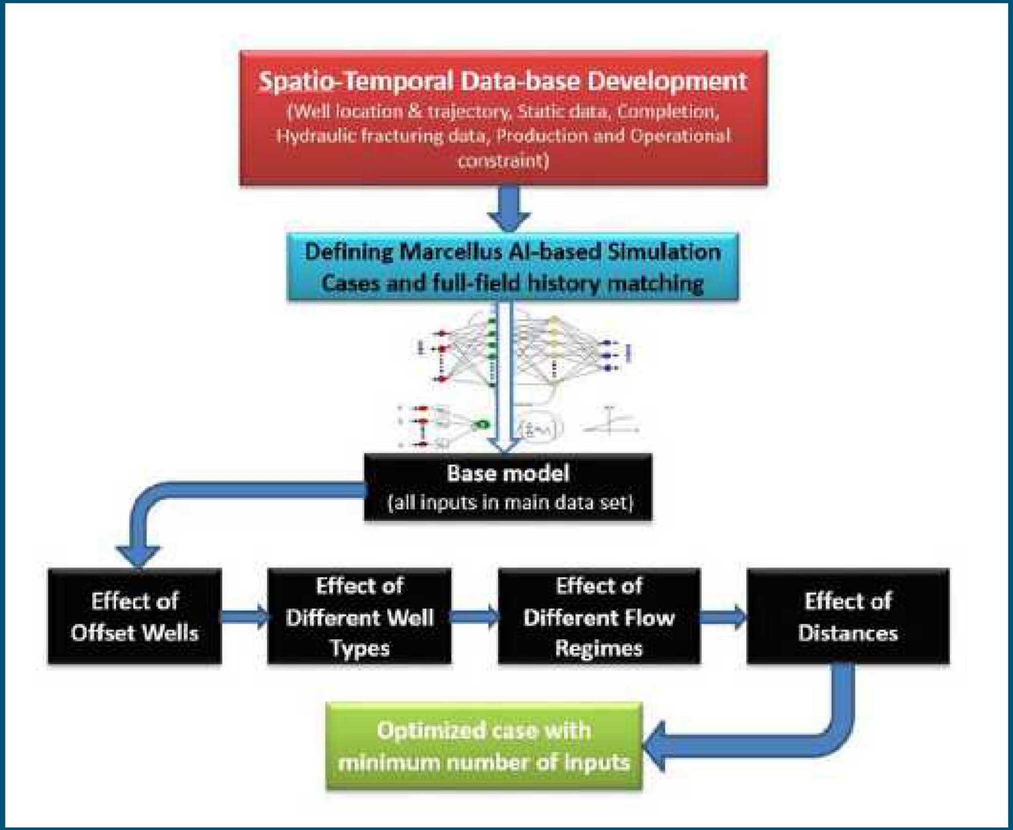

Fig. 4 Flowchart depicting the development of the proposed model [4]

Proposal

- Development of a predictive data-driven platform (PDDP) for subsurface energy systems
  - Use machine learning to model relationships among the physical properties of shale and fractures in order predict (1) cumulative production across time and (2) pressure distribution across space and time
- Current architectures being investigated:
  - Physics-Informed Neural Networks (PINN)
  - Artificial Neural Network
  - Convolutional Long-Short Term Memory
- My contribution:
  - Augment PDDP by researching effectiveness of hybrid Convolutional Neural Network (CNN) – Long-Short Term Memory (LSTM) Architecture

Methodology

1. Dataset
2. Data Input Methods
3. Modeling Spatio-Temporal Data
4. CNN-LSTM Architecture

Dataset

- Data used to model subsurface energy production was obtained using the MRST-Shale simulator
- The dataset contains five features:
  - *Permeability* – a measure of interconnectivity
  - *Porosity* – a measure of the void spaces
  - *Hydraulic conductivity* – ease with which media can move through fractures
  - *Bottom hole pressure* – pressure acting on the walls of the well
  - *Fracture aperture* – perpendicular width of the open fracture
- The dataset contains samples at 70 different time points across 32 total cases
  - Training and validation set – 29 cases
  - Test set – 3 cases

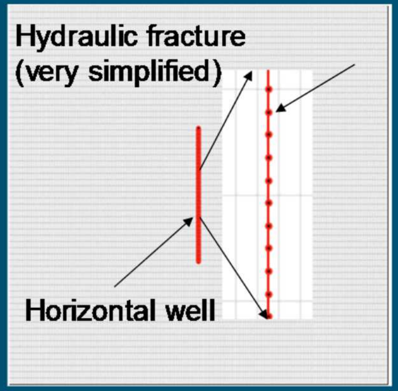

Fig. 5 Diagram of a horizontal well with a simplified hydraulic fracture

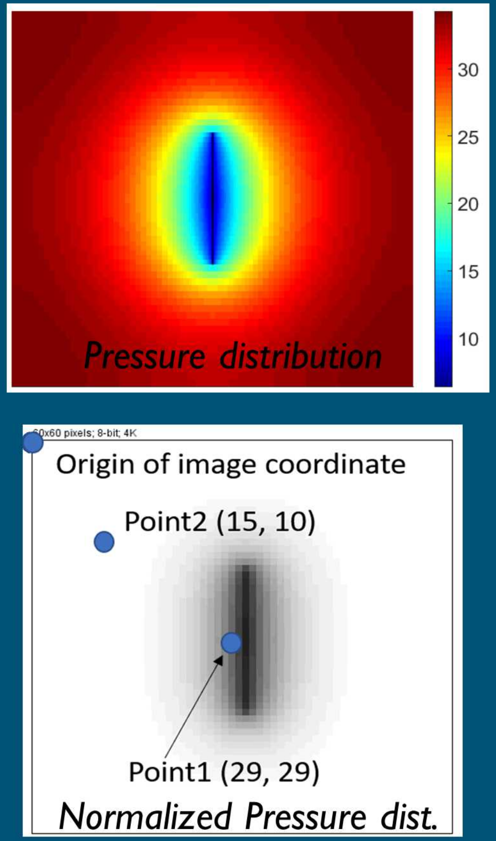

Fig. 6 Diagram pressure distribution data

Data Input Methods

- Different multichannel input methods for the case (feature) parameters were investigated
  - Data was scaled to values in the range [0, 1]
- Arbitrary input format
  - All case parameters are input to the model in a single 60x60 array, where parameters are stored in 'star'-shaped pattern
- Geometrically Intuitive input format
  - Each case parameter given its own channel
  - Layout of the parameter based on its physical characteristics

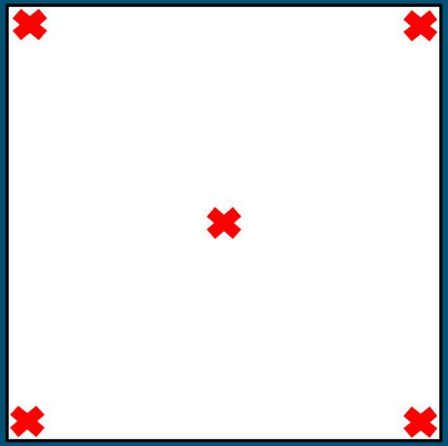

Fig. 7 Depiction of the how the case (feature) parameters are inserted into a channel when using the arbitrary input format

(a) *(b)*

Fig. 8 Masks used to facilitate the Geometrically Intuitive input method. Permeability and Porosity used mask *(a)*; Hydraulic Conductivity, Bottom Hole Pressure, and Fracture Aperture used mask *(b)*. White pixels denote value of 1; black pixels denote value of 0.

Modeling Spatio-Temporal Data

- Models must accurately represent the temporal evolution of spatial objects over time (e.g. tracking moving objects across video, etc.)

- Convolutional Neural Networks (CNN)
  - Algorithm is designed to take 2-Dimensional spatial inputs (i.e. images) and encode certain features/properties into the architecture

- Long-Short Term Memory (LSTM) Networks
  - A variant of recurrent neural networks, explicitly designed to learn long-term dependencies and to make predictions on temporal data

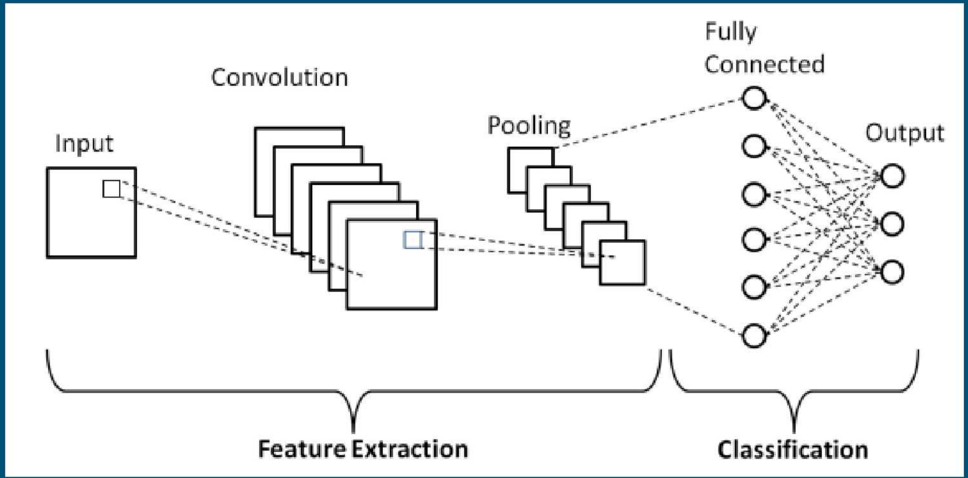

Fig. 9 Depiction of a basic CNN architecture [8]

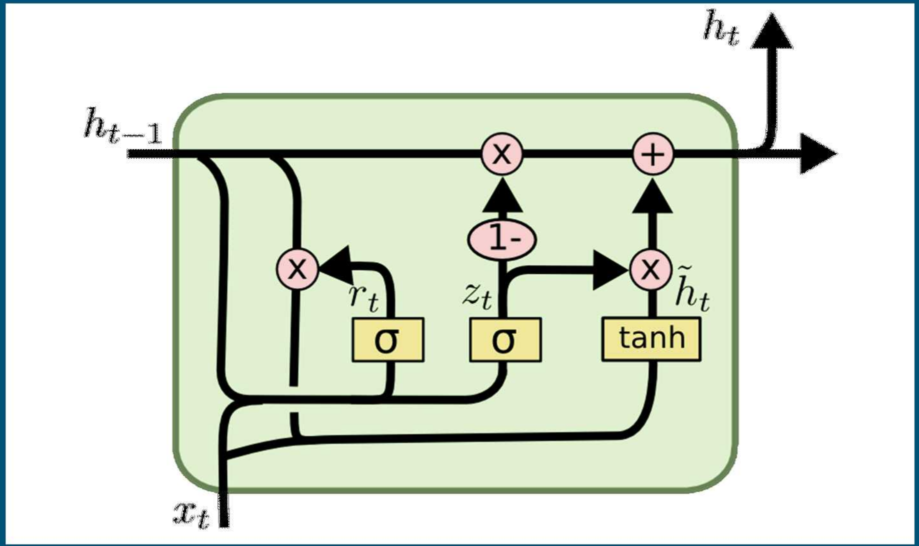

Fig. 10 Depiction of LSTM cell [12]

CNN-LSTM Architecture

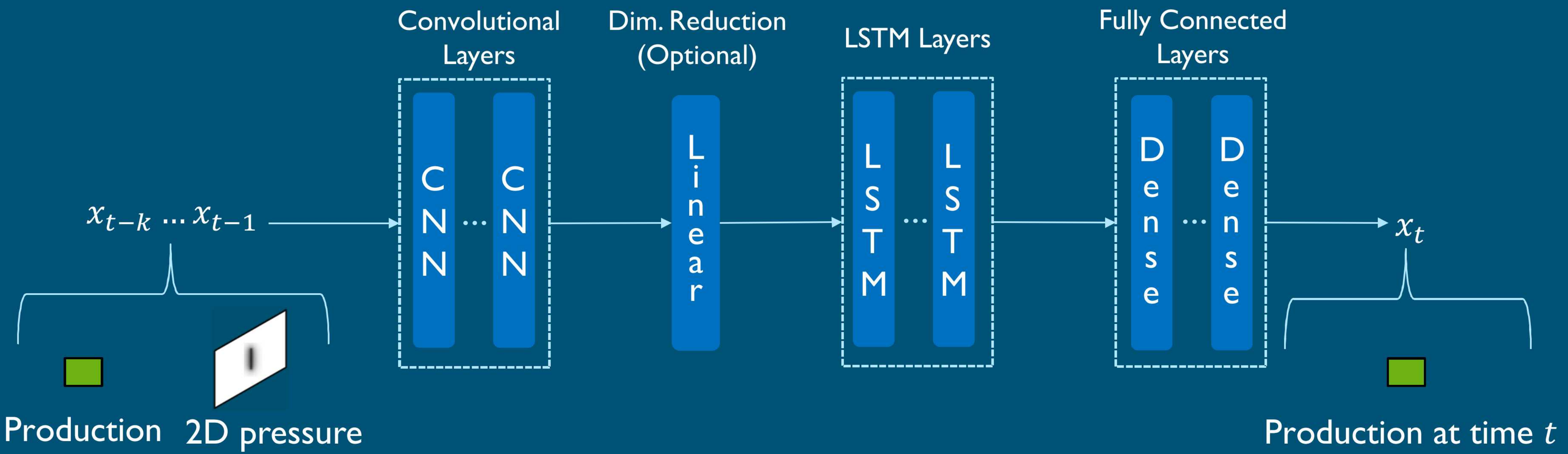

Fig. 11 CNN-LSTM-Dense architecture based on [1]

- Developed for visual time series prediction problems
- Previous work has applied architecture towards open research problems in
  - Speech recognition
  - Video recognition
  - Air pollution forecasting

CNN-LSTM Architecture (cont'd)

- Various Implementations and Model Considerations
  - Network specific parameters
  - Number of CNN Layers (e.g. ResNet-type architecture) and LSTM Layers
  - Dimension reduction (via additional Linear Layer) on extracted features
  - Multi-scale additions for short- and long-term contexts
  - Decoder for mapping to output

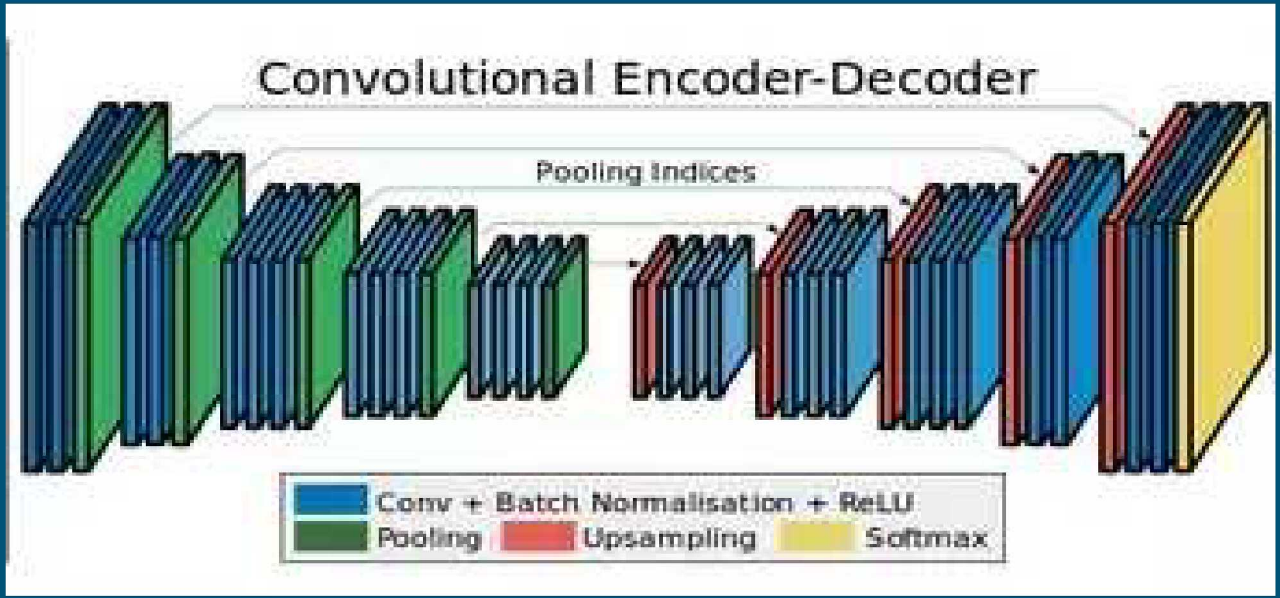

Fig. 12 Diagram of a standard convolutional encoder-decoder architecture [7]

Results

1. Cumulative Energy Production – Best Prediction
2. Pressure Distribution – Best Prediction
3. Optimizer Analysis
4. Data Input Method Analysis

Cumulative Energy Production – Best Model

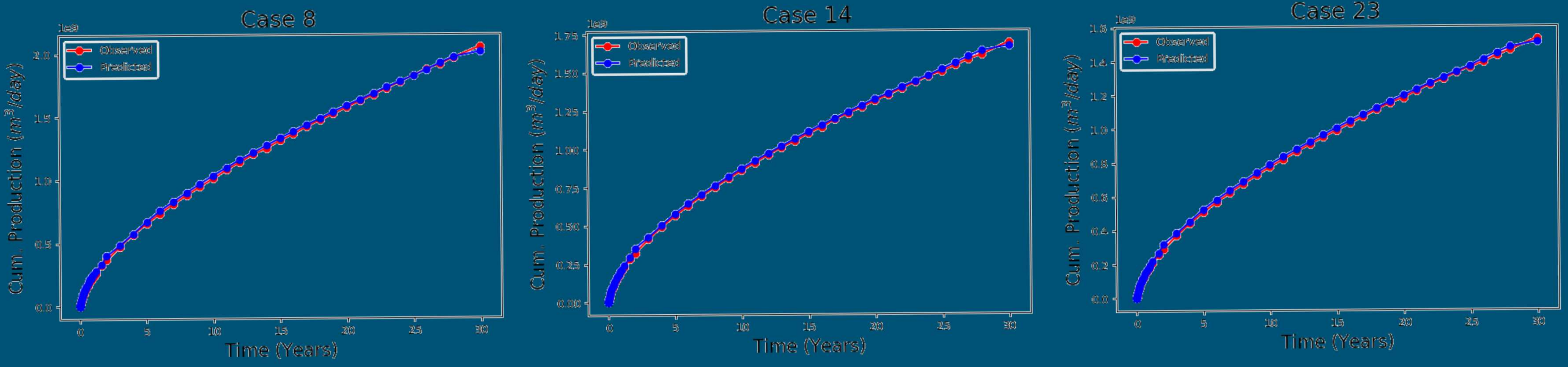

Fig. 13 Plot of prediction results from best model (blue) against observed production data (red) for test cases

Model Parameters	*CNN*			*LSTM*			*Dim. Reduction Layer*	*Output Mapping*	*Optimizer*	*Data Input Method*
	# of Layers	*# of Hidden Units*	*Kernel Size*	*# of Layers*	*# of Hidden Units*	*Stateful*				
Cum. Energy Production Model	5	128, 64	3x3, 1x1	2	128, 64	No	No	Dense	Adam	Arbitrary

Table 1 Specific model parameters used in best cumulative energy production model

Pressure Distribution – Best Model

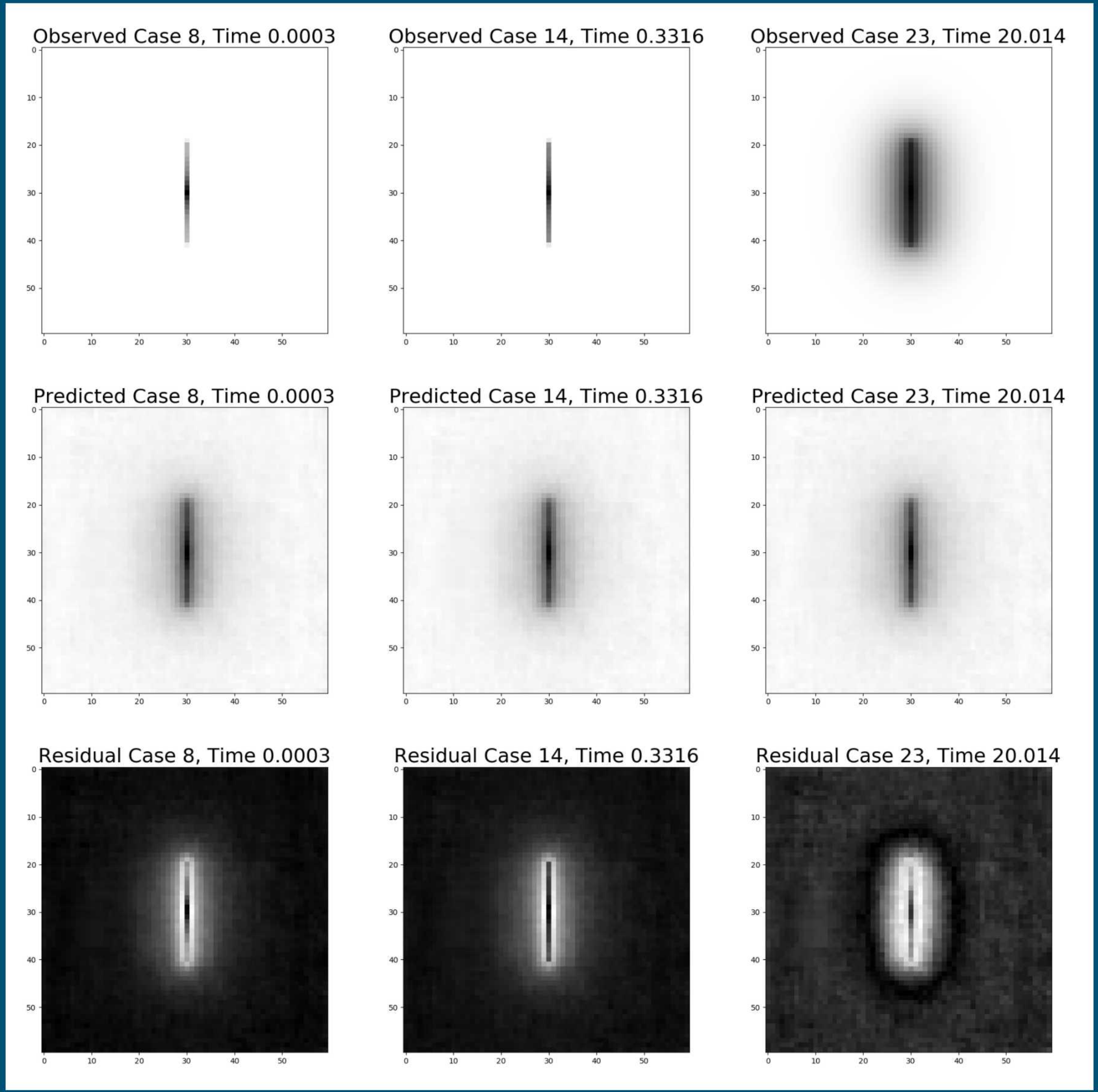

Fig. 14 Plot of observed pressure distribution data (first row) versus prediction results from best model (second row). Residual error are displayed (third row)

Model Parameters		***Pressure Distribution Model***
CNN	*# of layers*	3
	# of hidden units	16, 32, 32
	Kernel Size	3x3
LSTM	*# of layers*	1
	# of hidden units	64
	Stateful	Yes
Dim. Reduction Layer		No
Output Mapping		Decoder
Optimizer		NAdam
Data Input Method		Arbitrary

Table 2 Specific model parameters used in best pressure distribution model

Optimizer Analysis

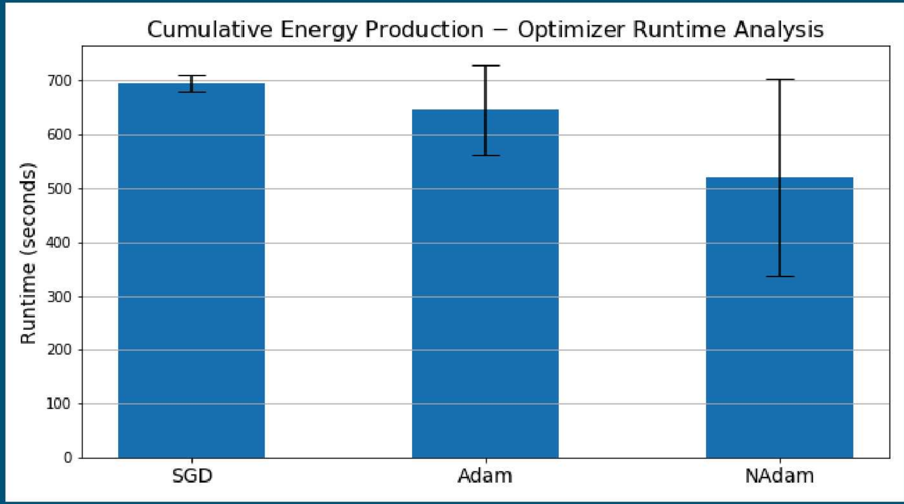

Fig. 15 Plot of training runtime, based on optimizer, from cumulative production prediction

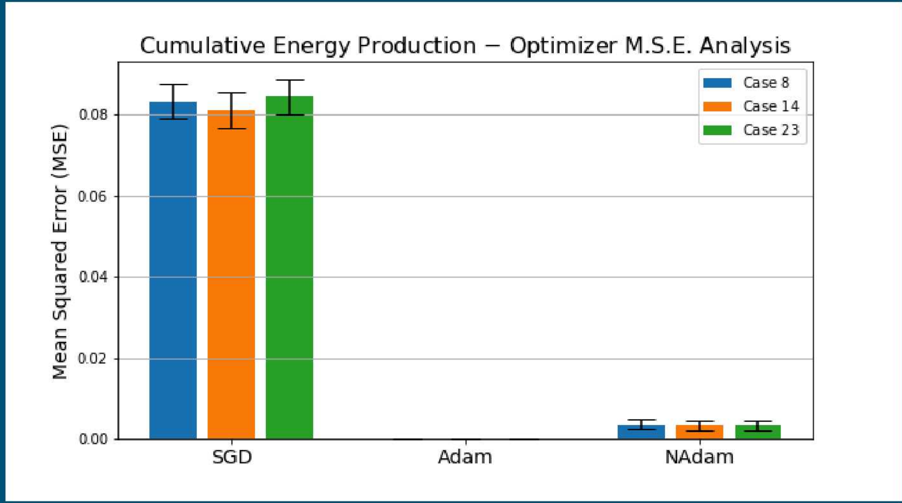

Fig. 16 Plot of Mean Squared Error (MSE) results, based on optimizer, from cumulative production prediction on individual test cases

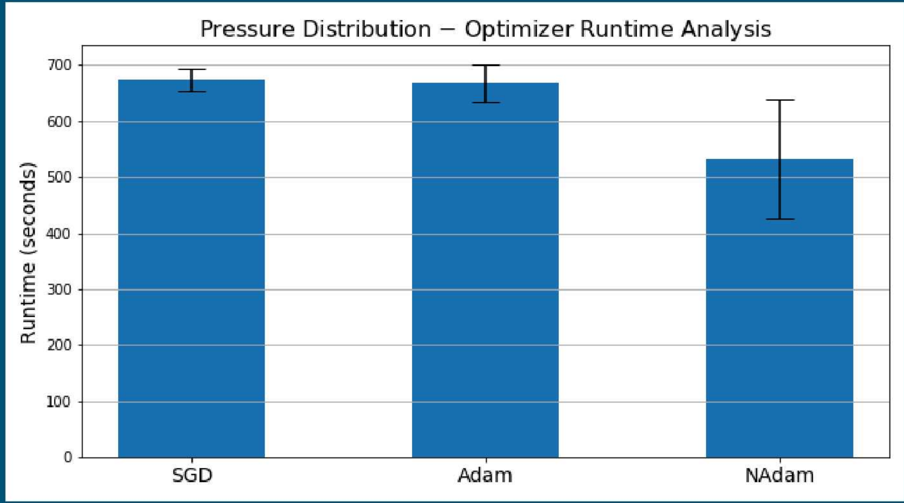

Fig. 17 Plot of training runtime, based on optimizer, from pressure distribution prediction

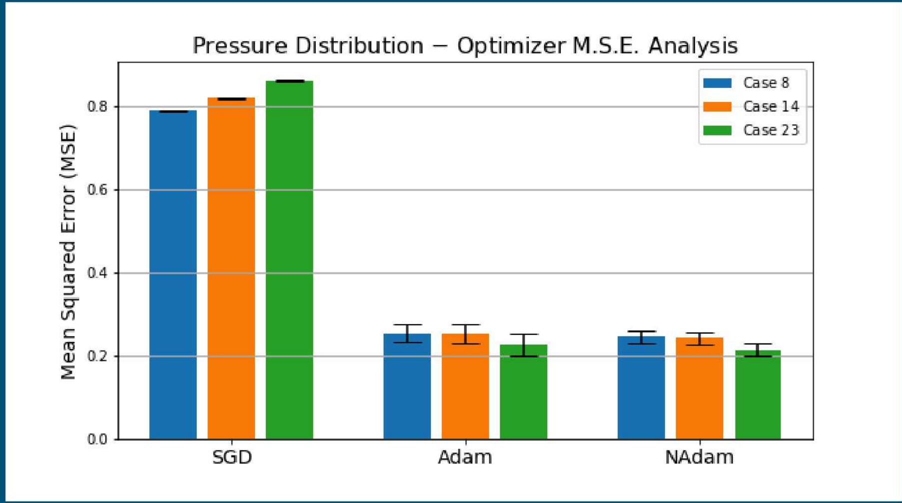

Fig. 18 Plot of Mean Squared Error (MSE) results, based on optimizer, from pressure distribution prediction on individual test cases

Data Input Method Analysis

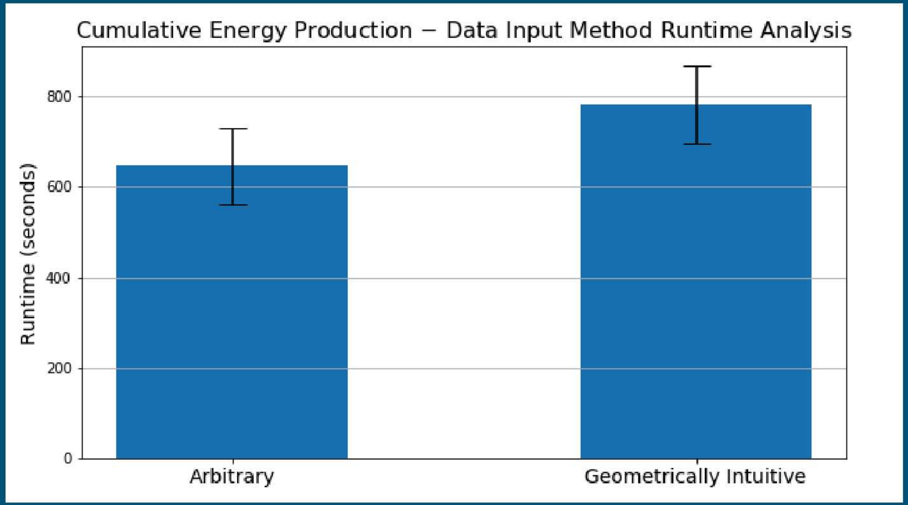

Fig. 19 Plot of training runtime, based on data input method, from cumulative production prediction on test cases

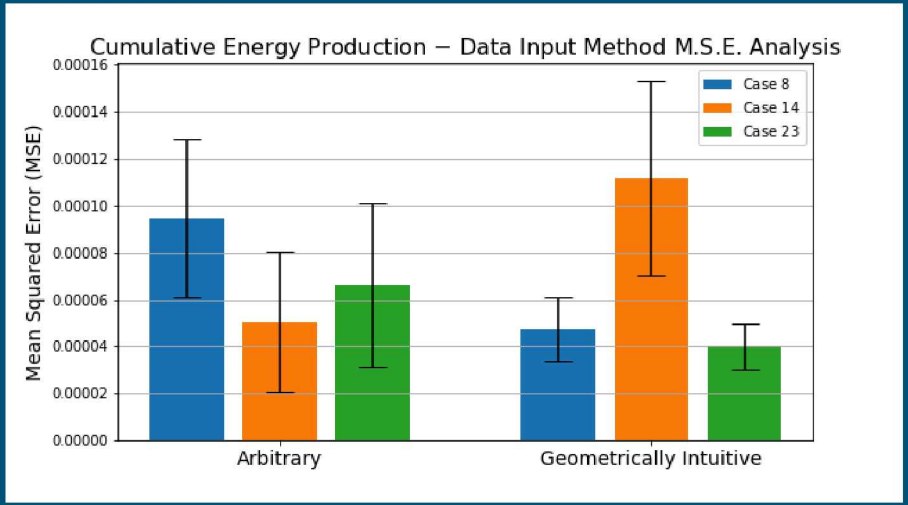

Fig. 20 Plot of Mean Squared Error (MSE) results, based on data input method, from cumulative production prediction on individual test cases

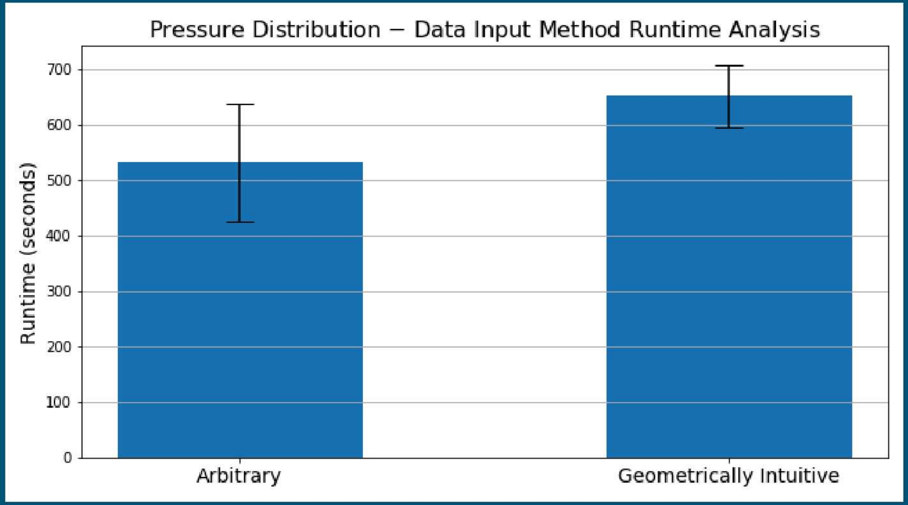

Fig. 21 Plot of training runtime, based on data input method, from pressure distribution prediction on test cases

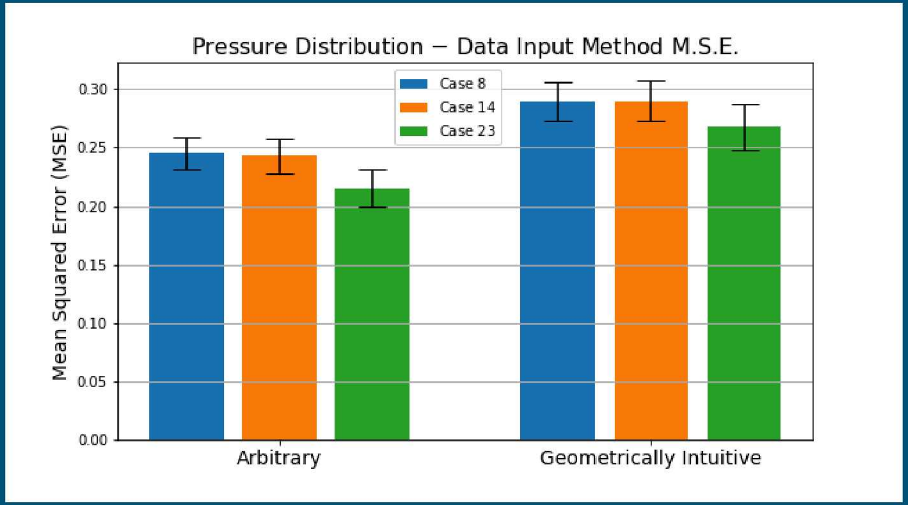

Fig. 22 Plot of Mean Squared Error (MSE) results, based on data input method, from pressure distribution prediction on individual test cases

Conclusion

1. Discussion and Limitations
2. Future Work

Discussion and Limitations

- Despite a relatively lightweight implementation, model obtained accurate performance when predicting cumulative energy production

- With respect to pressure distribution prediction, model has shown promising results with numerous avenues that can be investigated in order to increase model performance
  - Prediction may be limited due to the high variability in the central regions of the pressure distribution images
  - Overfitting may have occurred due to the complexity of the model
  - These issues could be resolved with a larger dataset

- Gained intuition regarding the use of different types of optimizers and with respect to data input format

Future Work

- Perform a complete ablation study on model parameters and data inputs and investigate various model considerations, including
  - Multi-scale additions for short- and long-term contexts [1]
  - Effect of stateful LSTMs
  - Deeper architecture with smaller layers vs less deep architecture with larger layers

- Perform an exhaustive parameter search in order to develop an optimized model

- Investigate similar hybrid model architectures, e.g. CNN-Bidirectional LSTM, CNN-HMM, Deep graphical models, etc.

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Questions?