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Hydraulic Fracture Design with a Proxy Model for Unconventional Shale Gas Reservoir with Considering Feasibility Study

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Abstract: Shale gas is a natural gas trapped in shale formation and is being actively developed in North America. Due to the low permeability of a shale gas reservoir in the range from 10^{-8} to 10^{-6} Darcy, horizontal drilling and multi-stage hydraulic fracturing are needed for its development. This paper presents a fast and reliable proxy model to forecast shale gas productions and an optimum hydraulic fracturing design for its development. The proxy model uses a robust regression scheme and can replace a commercial reservoir simulator. The proxy model proposed can determine the influence of impact factors on the production at each production time. The calculation speed of the proposed proxy model is about 1.4 million times faster than that of a reservoir simulator compared. The most economical hydraulic fracture design using the proxy model has a length of 168 m at each stage, which is determined by examining a large number of hydraulic fracturing designs considering economic feasibility.

Keywords: hydraulic fracture design; unconventional shale gas; proxy model; production optimization

1. Introduction

In the 2000s, since oil demands in China and India have increased and the oil price continues to rise, unconventional resources such as shale gas, shale oil, oil sand, tight gas, and coal bed methane have been actively developed. In the United States (US), the average production of shale gas in 2010 was 0.43 billion cubic meters per day (bcm/day). With continuous unconventional shale gas developments and technology innovation, it is increased by 3.5 times at 1.50 bcm/day in 2018.

Shale gas is a natural gas trapped in shale formation. Due to low permeability of shale formation, there are many difficulties in its development. Shale gas is actively developed by horizontal drilling and hydraulic fracturing technologies in the US. Its permeability is 10^{-8} to 10^{-6} Darcy, where fluid flow hardly occurs. Therefore, the most important factor in shale gas development and production is the multi-stage hydraulic fracturing to overcome its low flow capacity.

Multi-stage hydraulic fracturing is employed to increase the flow area between hydraulic fracture (HF) networks and shale gas reservoir formation. For its optimization, it is necessary to consider many characteristics of shale gas reservoir such as HF spacing and length, natural fracture networks, matrix permeability, adsorbed gas, and so on. However, the evaluation of productivity and economic feasibility study will require a lot of time and cost.

Many factors influencing shale gas production have been confirmed in some of the previous research. Mayerhofer et al. (2006) [1] integrated microseismic fracture mapping with a numerical production modeling of fracture networks in the Barnett Shale. The model matched production and pressure history data using fracture and matrix parameters. Cipolla et al. (2009) [2] used numerical simulations for complex fracture geometry and heterogeneity of shale gas reservoirs. However, it was very time-consuming. Valko and Lee (2010) [3] estimated reserves using a decline curve model for the production data in a tight gas reservoir. Since the decline curve model only utilized the trend of the production data, it cannot predict the change of production rate with different HF designs.

Biswas (2011) [4] developed a predictive model of shale gas production using transfer equations and mass balance equations. The model predicted the shale gas production using fluid saturation, fluid compressibility, temperature, storage pressure, and drainage area. However, natural fracture and matrix permeabilities were not taken into account in the properties of the shale reservoir. Yu and Sepehrnoori (2013) [5] proposed an optimal multiple horizontal well placement considering the influence factors of shale gas production using a response surface method for net present value (NPV). The response surface model was constructed using only 38 sample cases in the NPV prediction. The model with small training data cannot guarantee its predictive performance and may result in inaccurate results.

Xie et al. (2015) [6] rapidly predicted shale gas production using a fast marching method. However, a single porosity–single permeability model had limitations to simulate the pseudo steady state flow behavior of shale gas production. Kim et al. (2015) [7] analyzed the main influencing factors affecting the shale gas production, and then constructed a shale gas production prediction model using artificial neural network (ANN). However, in the case of this ANN model, it was difficult to show the weight of key influencing factors on the production. Balan et al. (2016) [8] conducted an optimization of hydraulic fracturing spacing for tight and shale gas reservoirs. However, only single HF was considered in the analysis.

Kim et al. (2017) [9] proposed a multi-objective history matching method with a proxy model for the characterization of production performances in the shale gas reservoir. The proxy model was employed for overcoming the time-consuming multi-objective method. However, the proxy model cannot handle the pseudo steady state flow behavior of shale gas productions. Tang et al. (2018) [10] developed a numerical simulation for multi-scale flow mechanisms in a shale gas reservoir. It can simulate various flow mechanisms such as gas desorption, the Klinkenberg effect, and gas diffusion. Although it may be good to duplicate shale gas behaviors in detail, the simulation cost is too high.

This paper presents an optimal hydraulic fracture design using a developed proxy model. The proxy model used a robust regression scheme and considered the change of the influence of the main variables affecting production at each production time. Its optimum design was selected by feasibility study with the development cost.

2. Methodology

Figure 1 shows the proposed workflow for the optimization of hydraulic fracturing design using the proxy model. To improve the accuracy of the proxy model, Latin hypercube sampling (LHS) and a robust regression model were employed.

2.1. Robust Regression for the Proxy Model

A proxy model is a prediction tool to replicate a full simulation model by considering key parameters. It has been used efficiently for the development plan, decision making, evaluation of uncertainty, optimization of operating conditions, and history matching in a hydrocarbon reservoir. Typical proxy models are regression model, response surface method, kriging, and ANN. A linear regression model is one of the oldest statistical methods. It is still employed in today's world of developing new statistical methods because a linear model is easy to understand while giving least variance among all linear estimation methods.

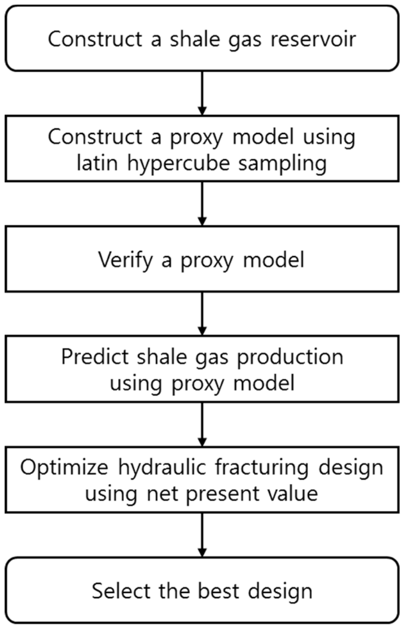


Figure 1. Flow diagram developed for this work.

The linear regression can be fit poorly if the error distribution is not normal, particularly when the errors are heavy-tailed. One scheme is to remove outlier observations. Another method, robust regression, is to use a fitting criterion that is not as vulnerable as least squares to unusual data. Robust regression estimators typically aim to fit a model that describes the majority of a sample. This estimator has the ability to provide accurate parameter estimate values in the presence of outliers or non-normally distributed errors. A few of the popular robust estimators are least absolute value (LAV) estimator, least median of square estimator, M-estimator, and MM-estimator.

In this research, M-estimator is employed for predicting shale gas productions because it is one of the most powerful tools for outlier adjustments, and a heterogeneous shale gas reservoir has many outliers in the data set. It can also identify key parameters on the shale gas production. M-estimator is defined as Equation (1) and minimizes the sum of residual function.

$$\min_{\beta} \sum_{j=1}^{N} \rho\left(e_j\right) = \min_{\beta} \sum_{j=1}^{N} \rho\left(y_j - x_j'\beta\right) \tag{1}$$

where ρ is the continuous symmetric function called the objective function with a unique minimum at 0 [11], e_j is the residual at time j, y_j is the cumulative gas production at time j, x are the influence parameters, and β is the regression coefficient of the parameters affecting the shale gas production.

2.2. Latin Hypercube Sampling

Sampling schemes can be typically divided into probabilistic and non-probabilistic methods. The former extracts a sample by assuming the occurrence probability of the target variable as the form of a probability distribution function. In addition, since all possible cases are considered by a probability distribution, the reliability of the result can be secured by many sampling. On the other hand, the other method does not assume a variable as a probability distribution.

Statistically, the more samples there are, the more meaningful the results are. However, fewer samples can reduce the experimental cost and time, if they are properly selected. Latin hypercube sampling is a method that can reduce the number of samples and simulations, and at the same time, it is complementing the disadvantages of the Monte Carlo sampling method, which cannot always perform uniform sampling. It also has the advantage of showing the characteristics of the population better as input variables are smaller [12]. If there are two variables such as in Figure 2, samples can be extracted so that each sample interval does not overlap. Figure 3 shows the comparison of sampling results between random sampling and LHS. LHS gives a uniform distribution than the random sampling. It prevents repeated samples in the sample space. Therefore, it is very useful in the case of high-cost and time-consuming experiments, since it selects relatively small number of samples. In this study, initial reservoir models for developing a proxy model are sampled by LHS.

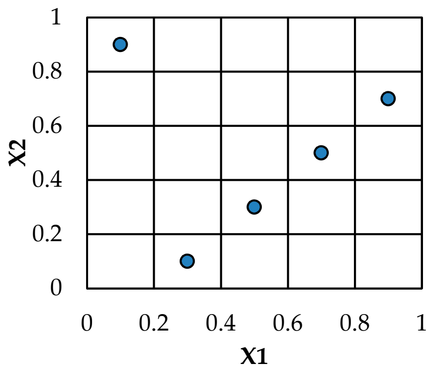


Figure 2. A Latin hypercube sample distributed uniformly on the unit square.

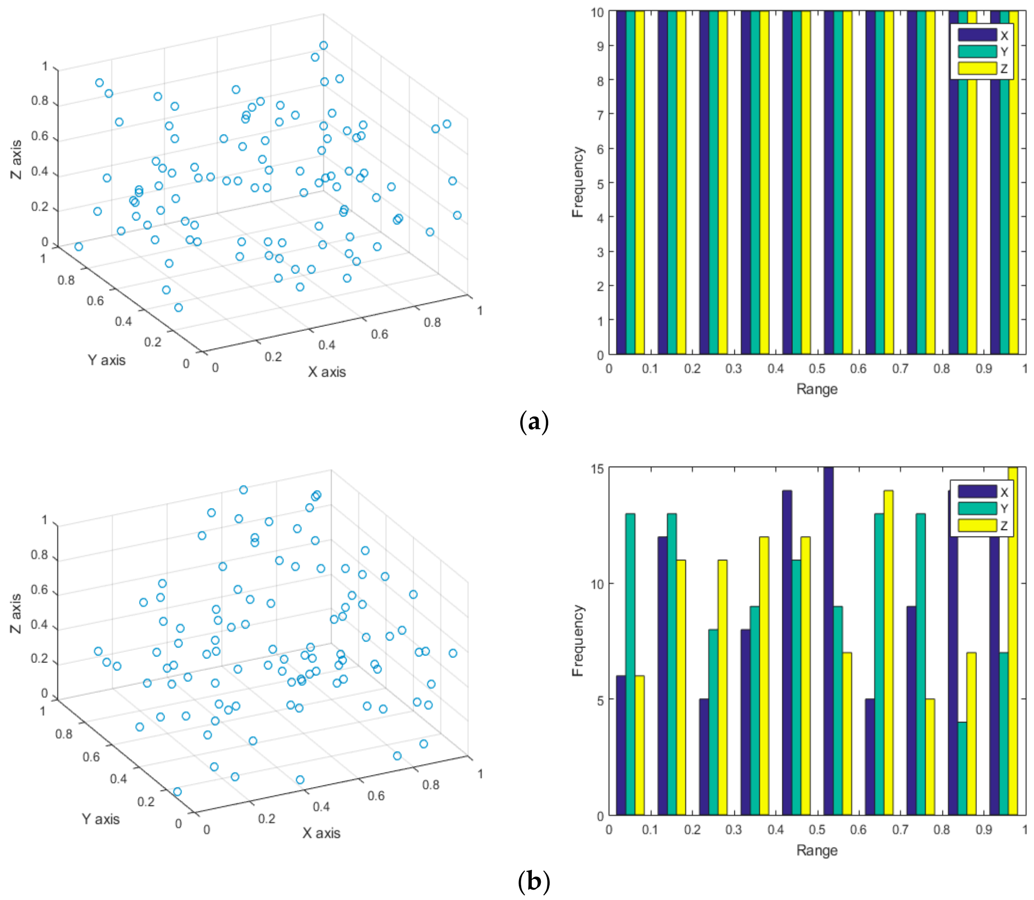


Figure 3. Comparison of the two sampling methods—(**a**) Latin hypercube sampling and (**b**) random sampling.

2.3. Dual Porosity–Dual Permeability Model

The important part of shale gas reservoir modeling is how to model natural fractures existing in the reservoir, because shale gas flows dominantly through the fracture system between the hydraulic and natural fractures. Typical models for replicating natural fractures are discrete fracture network (DFN) model and dual porosity–dual permeability (DPDK) model.

The dual porosity model shown in Figure 4 converts matrix, fractures, and vugs into homogeneous matrix and fracture. Then, it assumes that the matrix porosity and fracture porosity store the fluid and the fluid flows only through the fractures [13,14]. This model is simple, but it is difficult to explain the connection between the matrices [15], since most fluid flows through both the fracture and the matrix.

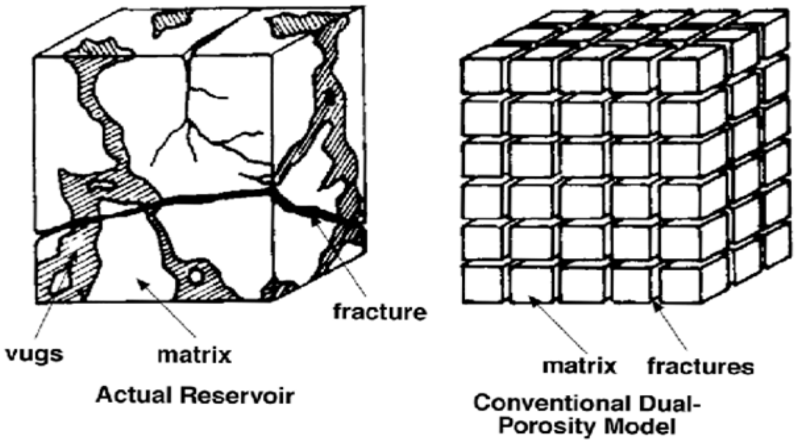


Figure 4. Idealization of a fractured reservoir [13].

The DPDK model can simulate the fluid flow in a matrix and a fracture. The fluid flow between the matrix and the fracture is affected by the matrix fracture coupling factor (σ) in Equation (2), which combines the fracture spacing in the x-, y-, and z-directions to account for the flow of the fluid in connected space in the reservoir. Since there are many fractures, the coupling factor becomes larger resulting in easier fluid flow. In this research, DFN model and DPDK model are used for modeling natural fractures in a shale gas reservoir.

$$\sigma = 4\left(\frac{1}{I_x^2} + \frac{1}{I_y^2} + \frac{1}{I_z^2}\right) \tag{2}$$

where I_x, I_y, and I_z are the fracture spacing in x-, y-, and z-directions, respectively.

2.4. Net Present Value

NPV is the value of all future cash flows over the entire time of an investment discounted to the present. It is a very important tool for financial decision making and is typically utilized for the development feasibility study. NPV can be compared for different cases to evaluate which one is advantageous in the long-term perspective. In this research, an objective function is NPV for the design of hydraulic fracturing considering the economic feasibility. For this, the shale gas production for each design is computed using the proxy model developed, and NPV is obtained by Equation (3).

$$\text{NPV} = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} - C_0 \tag{3}$$

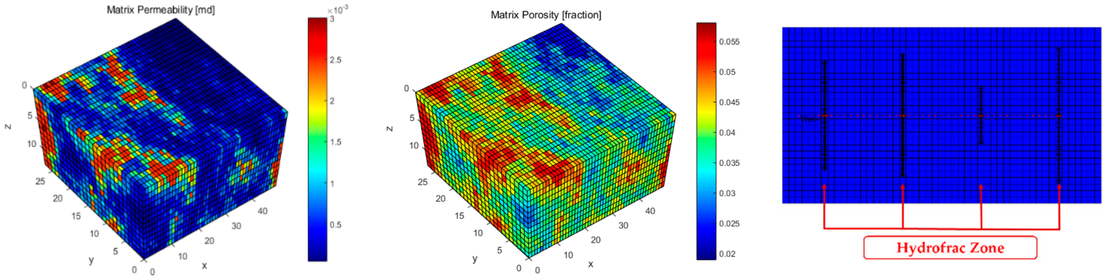
where C_t is the net cash flow at time t, r is the discount rate, and t is the period of the cash flow.

3. Results and Discussion

3.1. Computation of the Proxy Model

3.1.1. Modeling of the Unconventional Shale Reservoir

Figure 5a,b shows the matrix permeability and porosity distribution in a heterogeneous shale gas reservoir used in this study. The reservoir size is 899 m × 411 m × 79 m. The total grid number of the model is 49 × 27 × 13. The reservoir properties used for the numerical simulation are listed in Table 1. These properties are similar to those of Marcellus shale. Figure 5c shows a hydraulic fracturing design with four stages with different HF lengths.



(**a**) (**b**) (**c**)

Figure 5. Shale gas reservoir in 3D grid systems—(**a**) matrix permeability, (**b**) matrix porosity, and (**c**) hydraulic fracturing design.

Table 1. Input properties of the synthetic reservoir to computing the proxy modeling.

Input Parameters (unit)	Fixed Value	Uncertain Value
Depth (m)	2591	–
Reservoir size (x, y, z) (m)	(899, 411, 79)	–
Grid size (Δx, Δy, Δz) (m)	(15, 15, 6)	–
Reservoir pressure (MPa)	27.58	–
Bottomhole pressure (MPa)	3.45	–
Diffusion coefficient (m^2/day)	0.0047	–
Langmuir adsorption constant (1/kPa)	0.0073	–
Gas composition CH_4 (%)	100	–
Rock density (kg/m^3)	1922.22	–
Rock compressibility (1/MPa)	0.00015	–
Reservoir temperature (°C)	25	–
Number of hydraulic fracture stages	4	–
Average of matrix permeability (md)	5.82×10^{-4}	–
Average of matrix porosity (fraction)	0.037	–
Hydraulic fracture half-length (m)	–	(15–168)
Hydraulic fracture conductivity (md·cm)	–	(305–1524)

The natural fractures in the shale gas reservoir affect the connectivity of HF zones. Since they were closely related to the hydraulic fracturing plans, their modeling in the reservoir required many properties such as natural fracture density, direction, size, spacing, and their connectivity (Table 2). In this study, the DFN model was employed to simulate natural fractures for the shale gas reservoir (Figure 6a). Upscaling was used for adjusting the DFN model to the DPDK model (Figure 6). The final DPDK model was applied to replicate the simultaneous matrix-to-matrix and fracture-to-fracture flow in the reservoir.

Table 2. Natural fracture properties of the synthetic reservoir.

Input Parameters (unit)	Value
Trend (degree)	85
Plunge (degree)	15
Fisher constant	25
Fracture length (m)	Lognormal (52, 9)
Fracture intensity (m^2/m^3)	0.49
Model	Enhanced Baecher
Trend (degree)	85

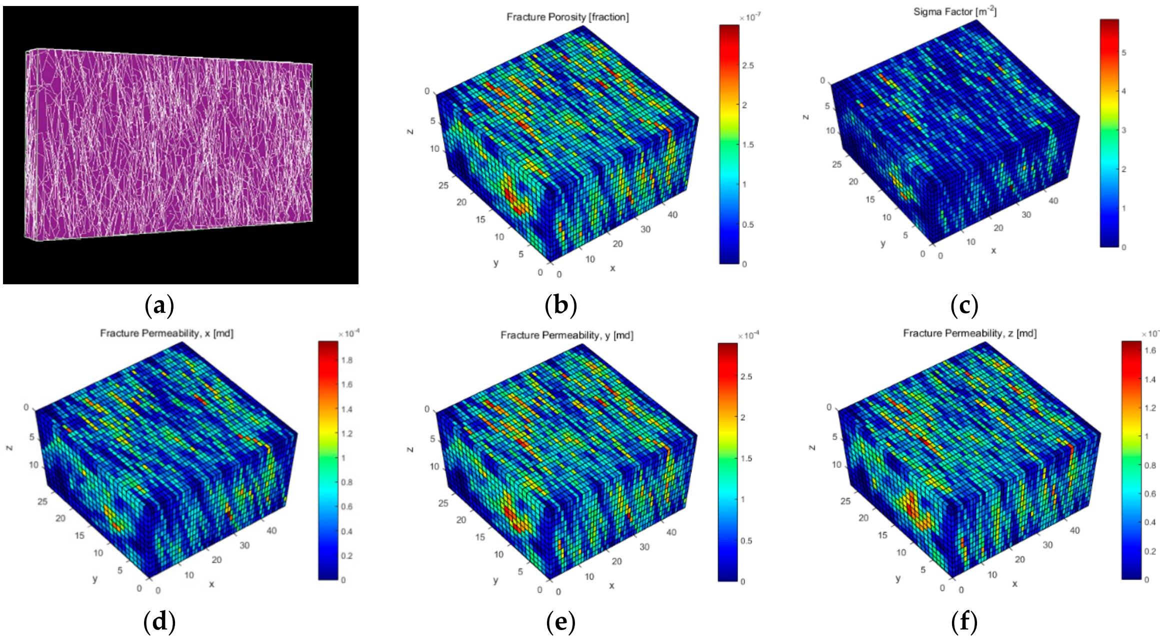


Figure 6. Natural fracture generation and upscaling in 3D grid systems—(**a**) natural fracture generation, (**b**) fracture porosity, (**c**) sigma factor, (**d**) fracture permeability, *x*, (**e**) fracture permeability, *y*, and (**f**) facture permeability, *z*.

3.1.2. Proxy Model Based on the Robust Regression

The key parameters used to create the proxy model are HF length and conductivity. Since shale gas reservoirs have very low permeability in the range from 10^{-8} to 10^{-6} Darcy, hydraulic fracture length and its conductivity are the most important factors in production [7]. In this research, the proxy model based on the two variables was developed for predicting shale gas productions. When the proxy model was constructed by fitting the robust regression model with the given data, its prediction accuracy was dependent on given data. Samples for the proxy model were 100 training data sets by LHS based on the properties shown in Table 1. We made additional 100 testing data sets using the same conditions to verify the proxy model.

The prediction performance of the robust regression based the proxy model was compared with that of ANN, which typically used a feed forward backpropagation network model for nonlinear prediction. For the ANN, 15 neurons made up the first hidden layer, 10 neurons made up the second hidden layer, and the production was the only parameter in the output layer. Data were divided into three sets—training (70%), validation (15%), and testing (15%). At the same time, the estimation error was computed using the mean absolute percentage error (MAPE) between a commercial simulator (CMG reservoir simulator) and the proxy model. The R^2 values showed the goodness of each model's fit.

Figure 7 is the cross plot between the commercial simulation and the proxy model. It is the average of the productions from the 100 training data. As seen, they provide an excellent match. In the training and testing data, the proxy model showed a better prediction performance than the ANN model. The accuracy of the proposed proxy model was MAPE of less than 3.4%, but that of the ANN model was 6%, especially for the testing sample data. The R^2 of the proxy model also appeared higher than that of the ANN model (Table 3).

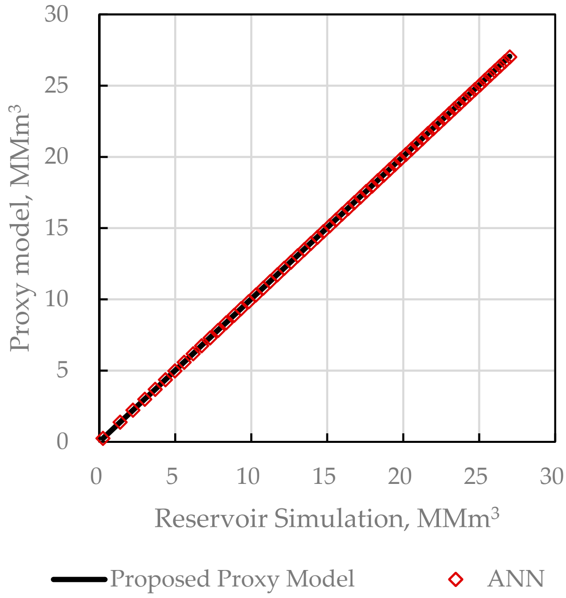


Figure 7. Cross plot of cumulative gas productions at each proxy model.

Figure 8 shows the average prediction errors of the ANN model and the proposed proxy model using 100 training and 100 testing data. For the prediction error according to the production time, the proposed method provided smaller errors, which decreased with the lapse of time. On the other hand, in the case of the ANN model, it was found that the prediction error moved in a random walk according to time. This was because the model fit of the ANN was different at each prediction point.

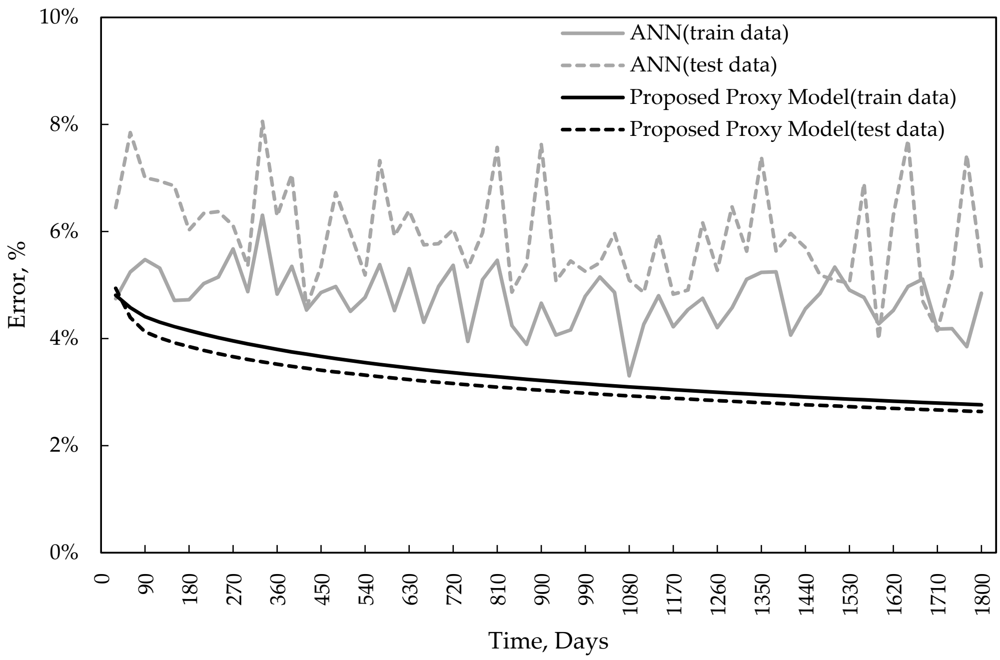


Figure 8. Prediction accuracy of artificial neural network (ANN) model and the proxy model.

Table 3. Comparison of prediction accuracy between the proxy model and ANN.

Type	MAPE	R^2
ANN (training data)	4.80%	0.988
ANN (testing data)	6.00%	0.980
Proposed Model (training data)	3.40%	0.995
Proposed Model (testing data)	3.20%	0.996

3.1.3. Sensitivity Analysis Using the Proxy Model

We can look at the influence of the variables by using the coefficients of the proxy model according to time change in the proposed model. Figure 9 presents the effect of each parameter on the shale gas productions. The ratio of importance was evaluated as the ratio of the coefficients from the proposed model. It showed that the HF length affected the production amount more than the HF conductivity.

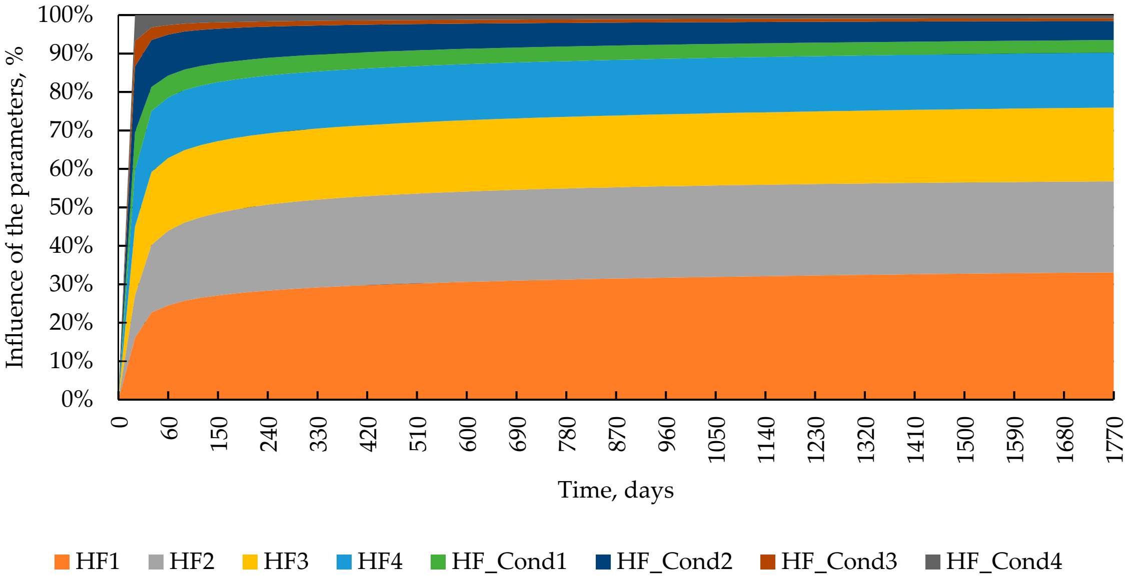


Figure 9. Influence change of each parameter. (HF#, hydraulic fracture length; HF_Cond#, hydraulic fracture conductivity; # = 1, 2, 3, and 4 denote the location of hydraulic fracture stage.)

Although it can be seen that the influence of HF conductivity was large in the early stage of the production, it decreased with time. This was because the gas flowed along the HF zone of higher permeability, and the volume of gas inside was restricted. Since its length had a large influence on the production of shale gas, in this study, hydraulic fracturing design was carried out in consideration of economy according to the HF length using the developed proxy model.

3.2. Optimization of Hydraulic Fracture Design

3.2.1. Assumptions for NPV Calculation

Even if the hydraulic fracturing stage has the same HF length, the gas production will be different due to the reservoir heterogeneity. In other words, the production volume varies depending on each HF length. Therefore, an optimal design was proposed considering the development cost of the shale gas. The stage of HF was four (Figure 10), and the 14,641 designs of the hydraulic fracturing were examined assuming that the HF length varied from 50 to 550 ft for each stage ($11 \times 11 \times 11 \times 11$) and HF conductivity was 30 md·ft.

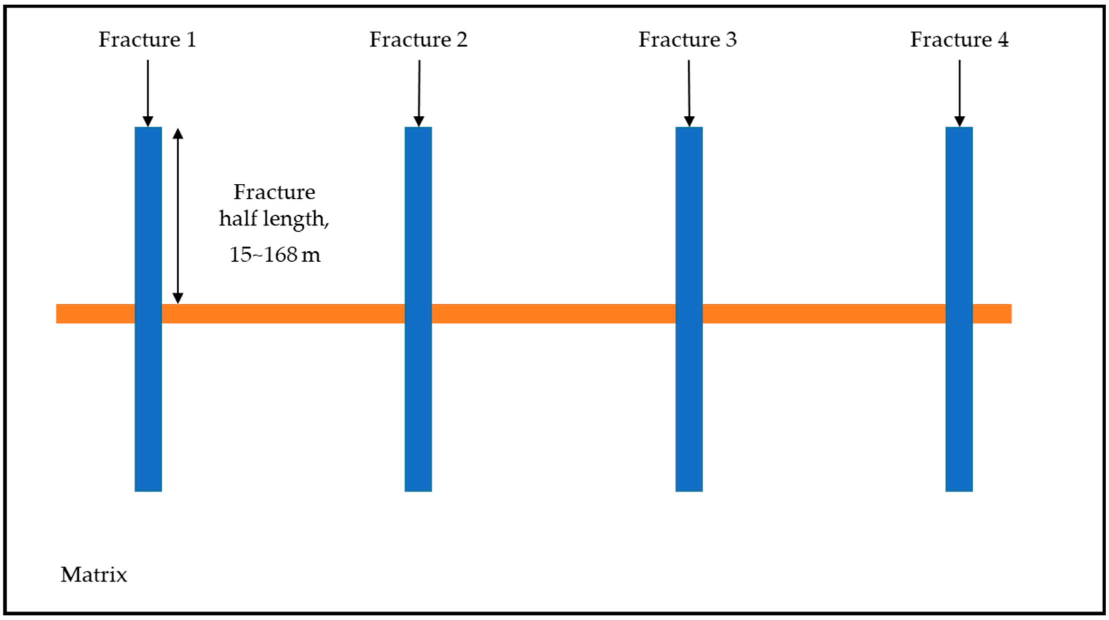


Figure 10. Schematic diagram of the hydraulic fracture design.

For comparing the computation time of the commercial software and the proxy model, it took 475 s to simulate one case by the commercial software (CMG), but it took just 0.000341 s for the proposed proxy model on a desktop with Intel Core 2 Duo CPU 3.30 GHz. The proxy model developed required just infinitesimal fraction of time compared to that of the full model. It was about 1.4 million times faster than the full simulator compared. Since it took a long time to simulate all cases using the commercial software, the proxy model was utilized for the optimization of HF design. Table 4 shows the economic data for the design.

Table 4. Economic data for net present value (NPV) calculation [16].

Horizontal Well Length (m)	Cost ($)	Hydraulic Fracture Half-Length per Stage (ft)	Cost ($)	Economic Parameter	Value
305	2,000,000	76	100,000	Operating cost	30 $/day
610	2,100,000	152	125,000	Gas price [1]	4.08 $/Mscf
915	2,200,000	228	150,000	Royalty	12.5%
1220	2,300,000	304	175,000	Interest rate	15%

[1] 2017 average price of natural gas (US EIA) [17].

3.2.2. Results of Hydraulic Fracture Design

Figure 11 shows the results of HF design based on NPV. It presents the NPV results for HF length as a boxplot. If HF cost was ignored, the longest fracture length would provide the highest NPV. Otherwise, another design would be chosen as the optimal one.

The highest and lowest NPVs of hydraulic fracturing design were 41.43 and 5.70 million dollars, respectively. The NPV difference between the two was 7.27 times. It was also found that the economic feasibility was different, even if the total length of HF was same, because the reservoir was heterogeneous and the total production varied depending on the degree of fracture network system.

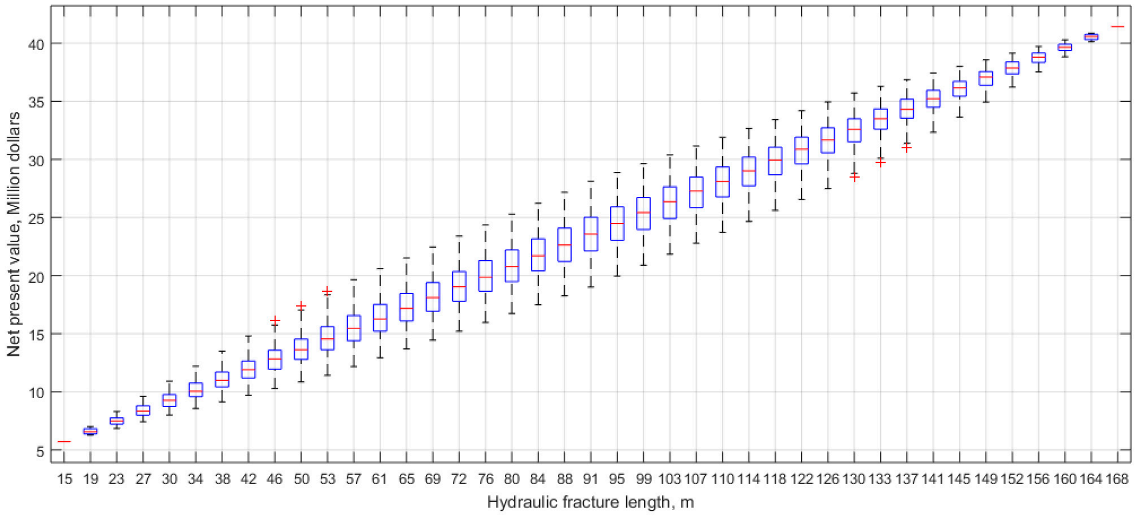


Figure 11. Net present values of each hydraulic fracture design.

4. Conclusions

In this research, we developed a proxy model for the optimization of shale gas hydraulic fracture design. As shale gas production can be quickly evaluated in the various hydraulic fracture designs, the proposed proxy model solves the time-consuming problem of shale gas reservoir simulation. Additionally, an optimum hydraulic fracture design could be selected by considering economic feasibility, even for a heterogeneous shale gas reservoir.

The results of this study are as follows. The shale gas reservoir was modeled by replicating the natural fractures and heterogeneous properties that are characteristic of an actual shale gas reservoir. The proxy model was developed by selecting the two key parameters of hydraulic fracture conductivity and hydraulic fracture length. For improving the prediction performance of the proxy model, LHS was employed to sample good and representative training data sets. It was found that its prediction performances for forecasting shale gas productions were much better than that of ANN model and its computing speed was tremendously faster than that of the commercial simulator. In additional, we could understand and explain the influence parameters in the proxy model.

For the optimization of hydraulic fracturing design with economic feasibility, it was found that its length of 168 m was the most economical. The procedure developed in this paper can be applied for a fast and economic design of hydraulic fracturing of heterogeneous shale gas reservoirs.

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Conflicts of Interest: The authors declare no conflict of interest.

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