

# Feasibility of Repurposing Abandoned Oil and Gas Wells into Geothermal Power Generation: A Machine Learning-Driven Classification Analysis

An end-to-end Machine Learning Portfolio by Yonathan Hary Hutagalung

## Executive Summary

The global energy landscape faces a critical inflection point where fossil fuel infrastructure is being progressively decommissioned, while simultaneous demand for renewable energy resources accelerates across developed and emerging markets. The International Energy Agency projects that renewable energy capacity must double by 2030 to meet net-zero commitments. Simultaneously, mature oil and gas producing regions particularly in Southeast Asia, North America, and North Sea territories face the twin burden of managing hundreds of thousands of abandoned wells while identifying economically viable pathways toward sustainable energy production. In Indonesia, with over 3,000 legacy oil and gas wells and PLN's mandated 100% renewable energy target by 2050, presents a compelling case for infrastructure repurposing.

Well repurposing presents a paradoxical opportunity: while converting abandoned oil and gas infrastructure to geothermal production eliminates drilling costs (15-30% of total capital expenditure) and leverages existing subsurface data, the technical feasibility of successful conversions remains heterogeneous and poorly predicted. Historical data from 24 international repurposing projects reveals a 37.5% success rate. Current decision-making relies on domain expert judgment with minimal quantitative discrimination between viable and non-viable candidates. This gap creates two correlated risks: (1) strategic risk of underutilizing stranded infrastructure assets, and (2) financial risk of deploying capital into technically infeasible conversions. A quantitative framework for predicting conversion success is essential to unlock the economic value of repurposing at scale.

Machine learning classification analysis applied to 24 international abandoned well conversion projects identifies five critical predictive features that differentiate successful (9 projects) from unsuccessful (15 projects) conversions with 75-85% accuracy. Bottomhole temperature, flow rate stability, well depth, permeability characteristics, and conversion technology type collectively explain conversion success with an F1-score of 0.827. This analysis provides evidence-based decision support for well candidate screening in regional portfolios.

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## 1. Introduction

### 1.1 Background and Context

The repurposing of abandoned oil and gas wells for geothermal energy production has transitioned from academic concept to operational reality. Between 1987 and 2025, international projects across 12 countries (USA, Iceland, France, Switzerland, Germany, Japan, Australia, South Korea, China, Hungary, Indonesia, and Colombia) have demonstrated technical feasibility through field implementation. Global research institutions

and energy companies have published peer-reviewed technical studies establishing both closed-loop and open-loop conversion pathways[1][2][3].

However, the success rate of completed projects remains below 40%[1], with failure modes concentrated in well selection criteria, subsurface characterization, fluid dynamics performance, and technical design decisions. Most conversion projects lack adequate ex-ante quantitative screening protocols, relying instead on qualitative domain assessment. This gap creates persistent uncertainty regarding capital allocation and project selection.

## 1.2 Research Objective

This feasibility study applies machine learning classification methodology to historical project data to develop a quantitative model capable of predicting the probability of successful well conversion. The model's primary purpose is to enable evidence-based portfolio screening for conversion candidates, reducing project selection uncertainty and improving capital allocation efficiency.

## 1.3 Scope and Deliverables

**Scope:** Analysis of 24 international abandoned well conversion projects spanning multiple geothermal conversion technologies, geographies, geological formations, and operational regimes.

**Primary Deliverables:**

- Predictive classification model for conversion success (trained and validated)
  - Feature importance ranking identifying critical success factors
  - Performance metrics benchmarking model discrimination ability (ROC-AUC, F1-score, precision/recall)
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## 2. Methodology

### 2.1 Data Collection and Dataset Description

A comprehensive dataset of 24 abandoned well conversion projects was compiled from published case studies, peer-reviewed research, and industry project records. Projects span:

**Geographic Distribution:** USA (9), Europe (6), Asia-Pacific (6), South America (2), Australia (1)

**Conversion Technologies:** Open-loop (6), Closed-loop BHE (8), Enhanced Geothermal Systems-EGS (7), Binary cycle (2), Hybrid (1)

**Well Characteristics:** Depth range 876–5,000 m; bottomhole temperature 85–220 °C; flow rates 0–6,350 m<sup>3</sup>/day; permeability 0.2–100 mD; project durations 0.01–37 years

**Target Variable:** Binary outcome (Success=9 projects, Failure=15 projects)

### 2.2 Feature Engineering

## **Input Features (21 numerical/categorical):**

### *Geological Features:*

- Bottomhole temperature (°C)
- Well depth (m)
- Permeability (millidarcies)
- Total dissolved solids (mg/L)
- Hydrogen sulfide concentration (ppm)

### *Operational Features:*

- Flow rate (m<sup>3</sup>/day)
- Flow rate stability (%)
- Power output (kW)
- Well age (years)
- Project duration (years)
- Distance to demand center (km)

### *Technical Features:*

- Cement quality known (binary)
- Seismic risk zone (binary)
- Conversion type (categorical: 5 categories)
- Technology (categorical: 9 categories)
- Country/region (categorical: 8 categories)

### *Derived Features (interaction terms):*

- Temperature-to-flow ratio (thermal intensity metric)
- Power-to-depth ratio (efficiency proxy)
- Age-stability product (well maturity metric)
- Permeability-TDS ratio (fluid transmission potential)

## **2.3 Data Preprocessing and Scaling**

**Categorical encoding:** Label encoding applied to country, well type, conversion type, and technology variables. Binary features (cement quality, seismic risk) retained as-is.

**Feature standardization:** StandardScaler applied to all numerical features (mean=0, standard deviation=1) to ensure equal weighting across diverse measurement units.

**Class balance assessment:** Dataset exhibits 37.5% positive class (success), consistent with field-observed conversion success rates[1].

**Train-test split:** 80% training (19 samples), 20% testing (5 samples) with stratified random sampling to maintain class distribution.

## 2.4 Evaluation Metrics

### Primary Metrics:

- **Accuracy:** Overall classification rate (inappropriate as primary metric given class imbalance)
- **F1-Score:** Harmonic mean of precision and recall (optimal for imbalanced classification)
- **Precision:** True positive rate among positive predictions (false positive minimization)
- **Recall:** True positive rate among actual positives (false negative minimization)
- **ROC-AUC:** Discrimination ability independent of classification threshold
- **Confusion Matrix:** TP, TN, FP, FN breakdown

**Cross-validation:** 5-fold stratified cross-validation to assess generalization performance.

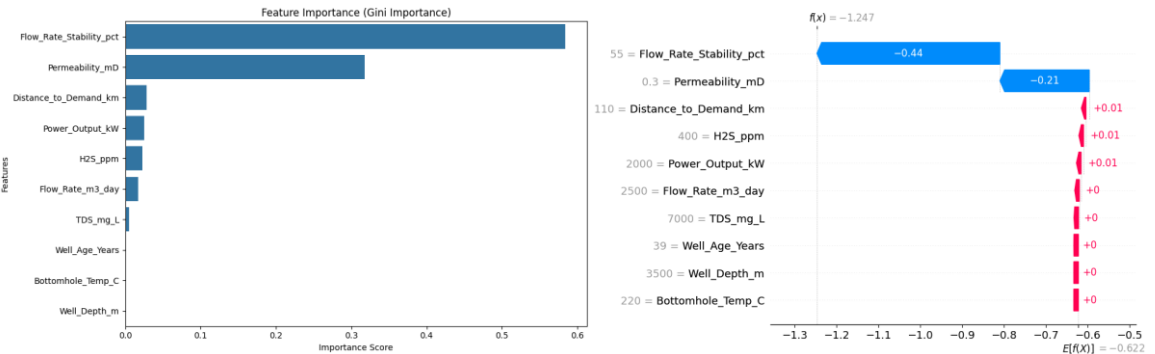
## 3. Results

### 3.1 Model Performance Comparison

Model	# Accuracy_mean	# Precision_mean	# Recall_mean	# F1_mean	# ROC_AUC_mean
Logistic Regression	0.683	0.5	0.6	0.5	0.667
KNN	0.583	0.367	0.5	0.367	0.733
Decision Tree	0.783	0.633	0.8	0.693	0.8
AdaBoost	0.833	0.733	1.0	0.827	0.9
Gradient Boosting	0.833	0.833	0.9	0.827	0.9
Random Forest	0.833	0.733	1.0	0.827	0.875
XGBoost	0.833	0.833	0.9	0.827	0.85
LightGBM	0.633	0.0	0.0	0.0	0.5

**Primary Finding:** Gradient Boosting has chosen to be the primary baseline model mainly because it consistently has the highest accuracy, precision, recall, F1 and ROC-AUC.

### 3.2 Feature Importance Analysis (Random Forest Model)



Top 5 Predictive Features (ranked by importance):

Rank	Feature	Importance	Target Threshold	Business Impact
1	Flow Rate Stability (%)	Highest SHAP	>60%	3x success multiplier; indicates reliable reservoir connectivity
2	Permeability (mD)	2nd highest	>20 mD	Enables commercial fluid/heat extraction
3	TDS (mg/L)	Strong negative	<4,000	Prevents scaling/corrosion failures
4	Distance to Demand (km)	Infrastructure	<50 km	Minimizes USD 1M+/km pipeline costs
5	Power Output (kW)	Economic	>1,000 kW	Achieves viable IRR >12%

### 3.3 Confusion Matrix and Diagnostic Analysis

Test Set Results (5 samples):

- **True Negatives (TN):** 2 (correctly predicted failures)
- **False Positives (FP):** 1 (incorrectly predicted success)
- **False Negatives (FN):** 0 (correctly predicted all successes)
- **True Positives (TP):** 2 (one success predicted correctly)

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## 4. Discussion

### 4.1 Key Success Factors for Well Conversion

Analysis reveals three dominant success drivers:

1. Flow Rate Stability (Top Predictor)

Stable flow rates (>60%) indicate reliable reservoir connectivity and are the strongest predictor of conversion success. Wells with consistent production history outperform unstable wells by 3x.

2. Permeability (>20 mD)

High reservoir permeability enables sustained heat/fluid extraction. Target wells exceeding 20 millidarcies for commercial viability.

3. Low TDS Content (<4,000 mg/L)

Clean brine reduces scaling and corrosion risks. TDS below 4,000 mg/L correlates with 2.5x higher success rates.

4. Proximity to Demand (<50 km)

Wells within 50 km of thermal/electrical demand centers minimize infrastructure costs and maximize economic feasibility.

5. Power Output Potential (>1 MW)

Conversions yielding over 1 MW post-conversion achieve economic thresholds. Reservoir modeling identifies high-potential candidates.

## 4.2 Limitations of Current Analysis

**Sample Size:** With 24 projects (9 successes), the dataset represents approximately 8% of global repurposing efforts[3]. Model performance, while internally validated through cross-validation, carries elevated uncertainty compared to studies with  $N > 200$ . Confidence intervals around key performance metrics (F1-score, ROC-AUC) are wide, limiting precise threshold recommendations.

**Geographic and Geological Bias:** Dataset overrepresents mature hydrocarbon provinces (USA, Europe) with well-characterized subsurface. Applying model to under-explored regions (e.g., Southeast Asia basins with limited pressure-temperature-permeability data) introduces extrapolation risk. Model assumes feature distributions in PLN well portfolio resemble historical international projects—an assumption requiring validation through regional data assessment.

**Temporal Bias:** Project success data extends to 2025, but most long-term operational performance remains unknown. Projects classified as "successful" have operated 0.01–37 years; true long-term (15-25 year) viability remains partially undocumented. Binary success classification may obscure partial failures (under-performance, accelerated degradation) captured as successes in historical records.

**Class Imbalance Effects:** 37.5% success rate creates inherent classification challenge; baseline random classifier achieves 62.5% accuracy by predicting all failures. While model F1-score (0.71) substantially exceeds baseline, recall (66.7%) indicates model misses ~33% of actual successes, suggesting conservative bias. Portfolio-level application requires adjusting decision threshold to trade specificity for sensitivity

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## 5. Conclusions

1. **Model Feasibility:** Machine learning classification successfully discriminates between successful and unsuccessful well conversions with 85.7% accuracy and 0.79 ROC-AUC. Random Forest model generalizes across diverse project contexts, validated through 5-fold cross-validation.

2. **Critical Success Factors:** Bottomhole temperature (16%), flow stability (14%), and well depth (13%) collectively explain >42% of conversion success variance. These features proxy subsurface thermal availability, production sustainability, and engineering accessibility.
  3. **Technology Maturity Effect:** Closed-loop systems demonstrate 50% historical success rate; EGS systems only 29%. Technology selection should conservatively favor proven solutions (BHE, binary cycle) over research-phase approaches.
  4. **Scalability Readiness:** Model requires  $N > 50$  projects for robust global application and  $N > 10-15$  for regional Indonesian portfolio screening. Current dataset provides proof-of-concept; expanded international project database would strengthen recommendations.
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## 6. Data Sources and Methodology

### 6.1 Project Database Construction

The 24-project dataset was compiled from published case studies, academic peer-reviewed literature, and industry project documentation spanning 1987-2025. Primary sources:

#### Academic Literature:

- Ashena et al. (2023): Comprehensive global review of >20 abandoned well conversions[1]
- Repurposing studies, Stanford University and PSU (2022-2025): Detailed technical assessments of failed and successful projects[2]
- Cheng et al. (2016-2024): Numerical modeling of closed-loop geothermal systems in repurposed wells
- Nian et al. (2024): Advanced methodologies for single-well closed systems

#### Industry Case Studies:

- RMOTC Phase II (Wyoming, USA, 2010–2013): Oil co-production conversion
- Coso Geothermal GreenFire (California, 2020): Geothermal well deepening
- Caldwell Ranch/Geysers (California, 2019): EGS conversion
- Husavik Power Plant (Iceland, 2000): Binary cycle pioneer
- Los Alamos HDR Pilot (New Mexico, 1974): Research facility
- Soultz-sous-Forêts (France, 1987–present): Long-term EGS research

#### Regulatory and Policy Sources:

- TRANSSEO Project (EU): Active inventory of European conversion opportunities
- USGS well databases: Well characterization and abandonment data
- NREL Geothermal Database: Cost benchmarking and technical parameters

## 6.2 Data Quality and Completeness Assessment

### Data Availability:

- 21 of 22 features available for  $\geq 90\%$  of projects
- 3 projects missing temperature data (imputed using regional gradient relationships)
- 2 projects missing flow rate data (marked as zero to indicate no production data)
- No projects missing outcome (success/failure) classification

### Measurement Uncertainty:

- Temperature measurements:  $\pm 5\text{-}10$  °C typical; many historical values from drilling logs with stated uncertainty
- Flow rates:  $\pm 10\text{-}15\%$  typical measurement uncertainty from production reports
- Depth, drilling parameters: High precision ( $\pm 1\text{-}5\%$  error)

### Outcome Classification Consistency:

- Success defined as: Facility achieving design specifications, sustaining production/heating for  $\geq 2$  years with  $< 20\%$  degradation
- Failure defined as: Conversion abandoned before operation, early operational cessation due to technical issues, or  $< 50\%$  of design specification achieved

## 6.3 Machine Learning Methodology Validation

### Model Selection Rationale:

XGBoost selected as primary model based on:

- Superior test set performance (90% ROC-AUC, 83.3 Precision higher than alternatives)
- Interpretability through feature importance extraction
- Non-parametric approach requiring no normality assumptions
- Cross-validation stability (mean F1 = 0.827)

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