**ABSTRACT**

Using historical data, time series forecasting attempts to estimate future values of a particular sequence. Researchers in the field of machine learning have recently been interested in this issue in order to solve the shortcomings of time-consuming, complex classical forecasting approaches. Particularly a powerful forecasting approach that infers the stochastic dependence between past and future values is greatly needed due to the rising availability of large volumes of historical data as well as the requirement to perform reliable production forecasting. In this article, we suggest a deep learning method that may overcome the drawbacks of conventional forecasting techniques and produce precise forecasts.

In place of the conventional recurrent neural network, the suggested method uses an artificial neural network design. Utilizing production data from a real oilfield in the Niger Delta, an assessment case study from the petroleum industry area was conducted. To make an objective assessment, the effectiveness of the suggested strategy is contrasted with a number of widely used techniques, either statistical or soft computing. The empirical findings reveal that the suggested model performs better than other conventional techniques using various measurement criteria.

**ABSTRACT**

It is never easy to anticipate the rate of production precisely in oil fields where direct monitoring of oil output is not practical. In such cases, empirical correlations and decline curve analytical methods are used to determine the oil production rate. When using these procedures, there may occasionally be significant errors made that lead to inaccurate results. The goal of this study was to forecast the rate of oil production by training the back propagation artificial neural network (BPANN) and decline curve analytical methods utilizing the Levenberg-Marquardt algorithm (DCAMs).

1600 data sets were taken into account in the study, with 70% used for training and 30% for testing. Gas production rate, tubing head pressure, and flowing bottom-hole pressure are employed as the input parameters, while crude oil production rate is the output. With regard to gas rate, production time, flowing bottom-hole pressure, and tubing head pressure, the created BPANN model makes predictions about oil production rate. In order to establish the most accurate approach for estimating the rate of oil production, the accuracy of the generated BPANN model and the DCAMs were evaluated. The mean absolute percentage errors for the BPANN and DCAMs (i.e., exponential, harmonic, and hyperbolic) predictions of oil production rates are 3.18, 9.27, 11.55, and 14.01, respectively.

The models' respective correlation coefficients were 0.9966, 0.9577, 0.9391, and 0.9578.

Compared to Decline Curve Analytical Methods, the BPANN model has a greater accuracy in predicting oil production rate.

**CHAPTER ONE**

**INTRODUCTION**

**1.1 Background of Study**

The prediction of oil production from the reservoir is a crucial step in the field of petroleum reservoir engineering. Under a variety of operating and maintenance scenarios, including well operations and completion, artificial lift, workover, production, and injection operations, this calculation of reserves entails a significant investment of money, time, and technology. The amount of oil in the reservoir needs to be estimated pretty precisely, however the geological and fluid parameters of the reservoirs are highly heterogeneous and nonlinear. As a result, it is challenging to predict the future oil production accurately. Numerous static and dynamic factors, including rock porosity and permeability (static parameters), reservoir pressure, and fluid saturation, affect how much oil is produced from a reservoir.

The forecasting of oil output from a reservoir would be more precise with these static and dynamic factors accessible. All of the parameter data aren't usually available, though. The accuracy of forecasting is decreased by the restricted data access from the oil fields.

Various forecasting approaches, including soft computing technologies and decline curve analysis, have been developed in the past (Tamhane et al., 2000). Because of their ability to deal with nonlinearities and time-varying conditions, artificial intelligence techniques including genetic algorithms, fuzzy inference systems, and neural computing have been widely used in the petroleum industry (Mohaghegh, 2001).

The capacity of neural networks (NN) to learn and adapt to new dynamic contexts makes it one of the most appealing artificial intelligence techniques for dealing with nonlinearities in parameter estimation (Aminzadeh et al., 2000) as well as in production forecasting (Weiss et al., 2002). Many studies have demonstrated the effective use of NN in the field of oil exploration and development, including pattern recognition in well test analysis (Al-Kaabi and Lee, 1993), reservoir history matching (Maschio et al., 2010), prediction of phase behavior (Habiballah et al., 1996), prediction of natural gas production in the United States (Al-Fattah and Startzman, 2001), and reservoir characterization by mapping the complex nonlinear in reservoirs (Mohaghegh et al., 2001).

**1.2 Statement of the Problem**

The oil and gas sector places a lot of importance on quantifying uncertainty. Production projections and reserve estimations will always contain some degree of uncertainty, which can be rather significant early in an oil and gas well's production life. Overconfident and pessimistic estimates of reserves and profitability might result from incorrect measurement of uncertainty.

McVay and Dossary (2014) claim that even little overconfidence and optimism can result in a portfolio's performance falling short by more than 30%. Early reserve and resource evaluation is crucial for the best possible development. According to McKinney et al. (2002), a suboptimal development strategy might cause 50% of potential asset value losses.

The most used technique for estimating reserves and forecasting production performance is decline curve analysis (DCA). But certain wells exhibit complicated characteristics, and as a result, the decline curve does not accurately reflect the production history.

Supertight shale formations and water-flooded oil and gas fields are two examples. Alternative approaches are needed to evaluate the uncertainty in production forecasts and reserves estimations in these situations when deterministic projections of future output and reserves might differ greatly from the actual values.

Most oil corporations employ simulation to do this. This approach is accurate, but it takes a long time since it takes a lot of computing resources to do the work. In this study, the researcher propose an alternate strategy that will considerably simplify this phase and drastically cut the required processing resources. The contrast between simulation and our suggested solution to this issue, using an AI model, is shown in Figure 1 below.

**FIGURE**

While simulation procedures take a lot of time and provide uneven accuracy, our approach makes reliable predictions quickly without sacrificing precision. The given dataset will enable the AI system to generate these predictions using machine learning (ML) and Deep Learning (DL), and the trained system will enable the AI to anticipate the output of oil wells based on a few geological parameters.

**1.3 Aim and Objective**

**Aim:**

The aim of the study is to forecast oil output from reservoirs using artificial neural networks.

**Objectives:**

The following goals will help to accomplish the aim of this research project.

1. Creation of reliable artificial neural network models that can accurately predict production over the field's useful life. It must be possible for the resilient neural network models to forecast oil output while taking changes in reservoir characteristics and well configurations into account.
2. Utilizing field data to validate ANN models and ascertain their predicting accuracy and constraints.

**1.4 Significance of the Study**

An estimate of the gross and net quantities (oil, gas, and water) that are anticipated to be generated from a hydrocarbon accumulation during the course of the accumulation's remaining life, as well as the fluids injected to create these volumes, is known as a production forecast (water, gas, and steam). (Petrowiki, 2016). Production forecasts are a critical component of petroleum engineering and geology. Production forecasts are used to determine the long-term viability of a field, as well as its potential to become an economic assets.

Production engineers may identify anomalous values and any defects in large oil well systems by using accurate oil production flow rate predictions to spot unusual values. (George, 2021) One of the most challenging tasks in production engineering is predicting oil production flow rates. This requires accurate data about the well geometry, reservoir properties, and fluid flow behavior. The Volve Field case study provides a real-world example where we can use artificial neural networks (ANNs) to make predictions on oil production flow rate from measurements taken at various stages of development.

**1.5 Scope of Study**

The goal of this project is to estimate the output of an oil well given a set of well characteristics that are utilized as independent variables, such as the rate of gas production, the pressure in the tubing, and the pressure in the flowing bottom hole, while the rate of oil production is kept constant. Following that, it utilizes 30% of the datasets for testing and validation and 70% of the datasets from a field in the Niger Delta for training. In the Python Google Collab environment, the code was tested. Two separate approaches were used to complete the project:

1. The regression approach, which forecasts data using linear regression, and
2. Artificial Neural Networks (ANN)

**References**

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