BAUERBERG KLEIN

TRAINING & CONSULTING

Harness Upstream Geophysical and Petrophysical Data with AI Workflows

INDEX

MODULE 01 Introduction: Data-driven Geophysical and Petrophysical modeling using AI techniques

MODULE 02 Exploratory Data Analysis: Upstream Data Exploration and Explanation

MODULE 03 Data Preparation for AI: Upstream Data Augmentation and Feature Engineering

MODULE 04 Machine Learning Techniques: Supervised and Unsupervised in E&P

MODULE 05 Deep Learning Techniques: Upstream E&P Deep Learning

MODULE 06 Case Studies: Completion Strategy and Automated Tops

INDEX

MODULE 07 Case Studies: Seismic Attributes

MODULE 08 Case Studies: Drilling Program & Completion Study and Virtual Assistant for Fluids and Lithology

MODULE 09 Case Studies: Forecasting Principles & Production Forecasting Techniques

MODULE 10 Case Studies: Time-Series Analysis and Production Forecasting

MODULE 11 Digital Twins: Upstream E&P

MODULE 12 PINNs: Physics-Informed Neural Networks & Explainable AI and Generative AI

Module 09

Case Studies: Forecasting Principles & Production Forecasting Techniques

LEARNING OBJECTIVES

- ➢ GOAL01: Forecasting - Six Principles
- ➢ GOAL02: Forecasting Techniques & Forecasting Data-Driven Workflows
- ➢ GOAL03: Case Study: NOC Re-engineering Brownfield

Case Studies

Six Principles of Forecasting

1. Forecasting is a stochastic problem
2. All forecasts are wrong
3. Some forecasts are useful
4. All forecasts can be improved
5. Forecast accuracy is never guaranteed
6. Having a second opinion is preferred

Case Studies

Production Forecasting

A time series is a sequence of observations *Y1*, … *Yt-1*, *Yt*, where the observation at time *t* is denoted by *Yt*.

Rule Induction for TS Forecasting

- Exponential Smoothing (ES)
- Auto-Regressive Integrated Moving Average (ARIMA)
- Random Walk (RW)
- Neural Networks (NN)

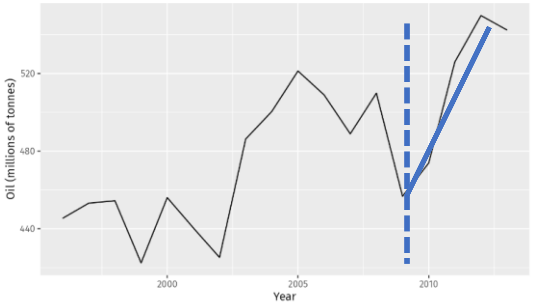
Case Studies

Exponential Smoothing

Simple and low cost
- Less Data Memory Storage
- Fast Computational Speed

Not as accurate:
- ARIMA
- FFNN

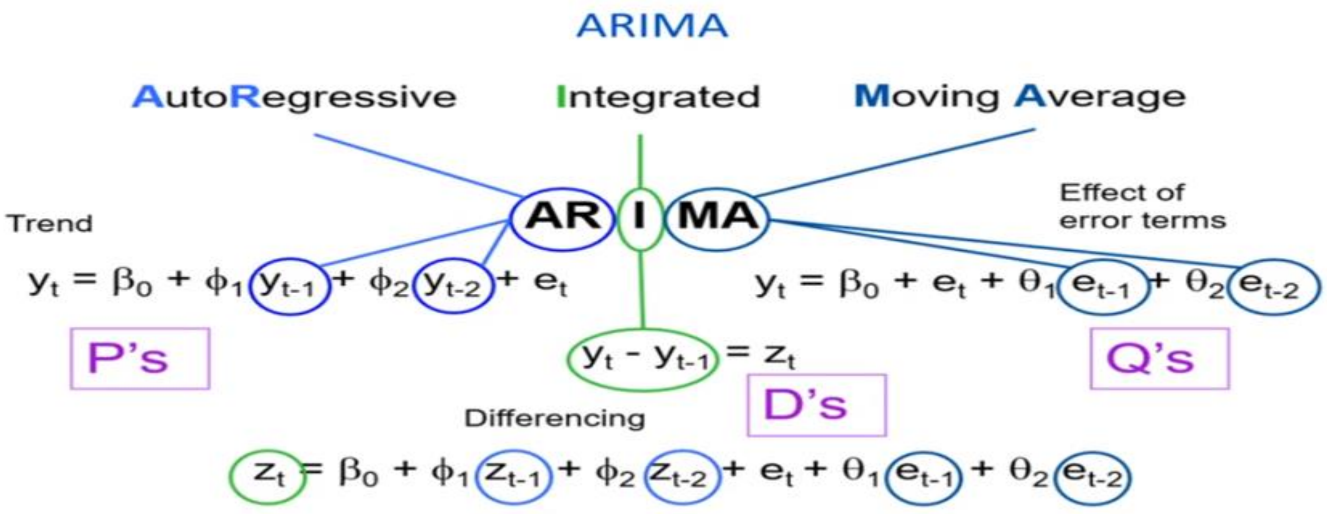
- **Simple Exponential Smoothing (SES)**
- Double Exponential Smoothing (DES)
- Triple Exponential Smoothing (Holt-Winters Method)



Oil Production in Aramco from 1996 - 2013

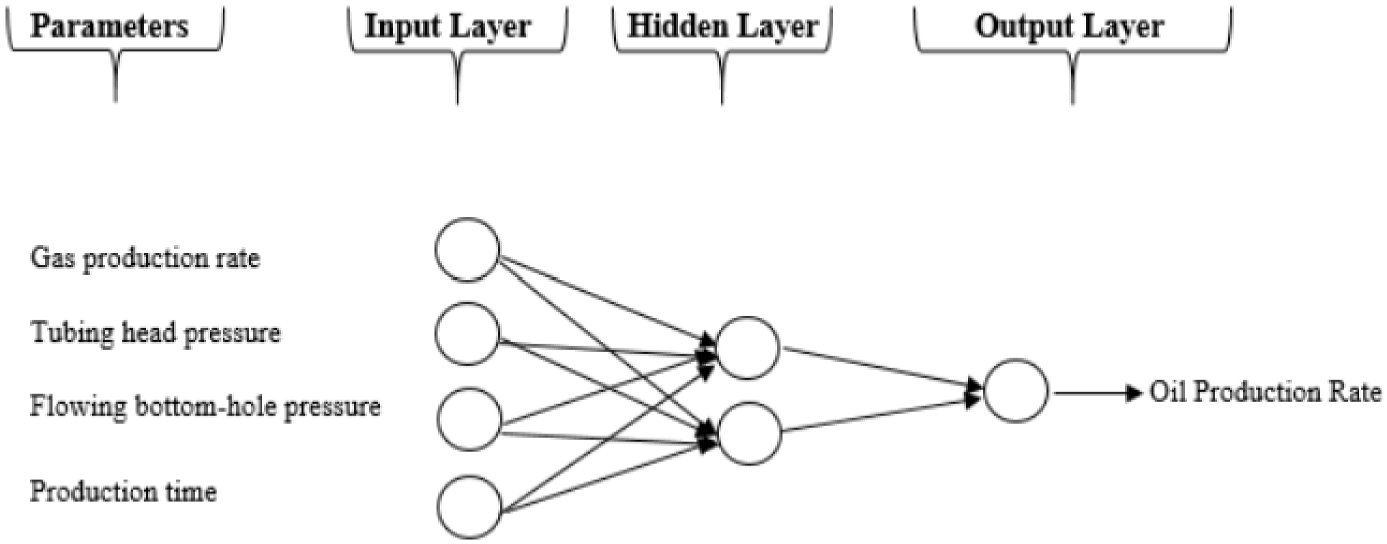
Case Studies

AutoRegressive Integrated Moving Average



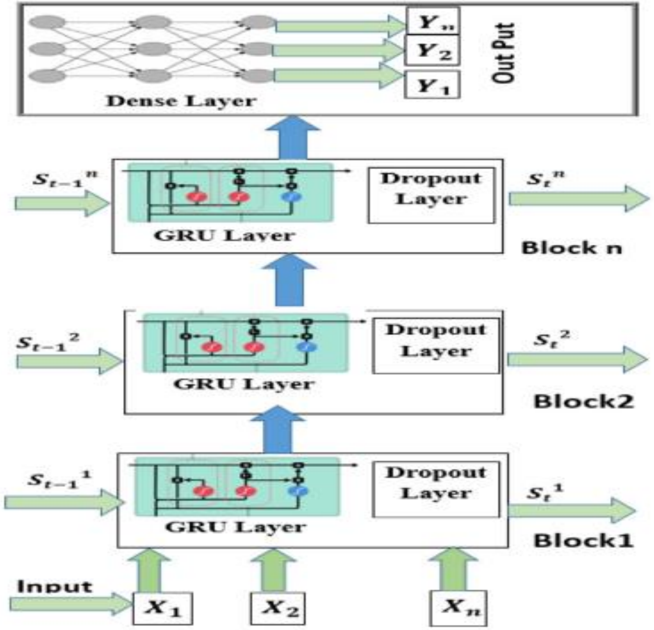
Case Studies

Artificial Neural Networks - ANNs



Case Studies

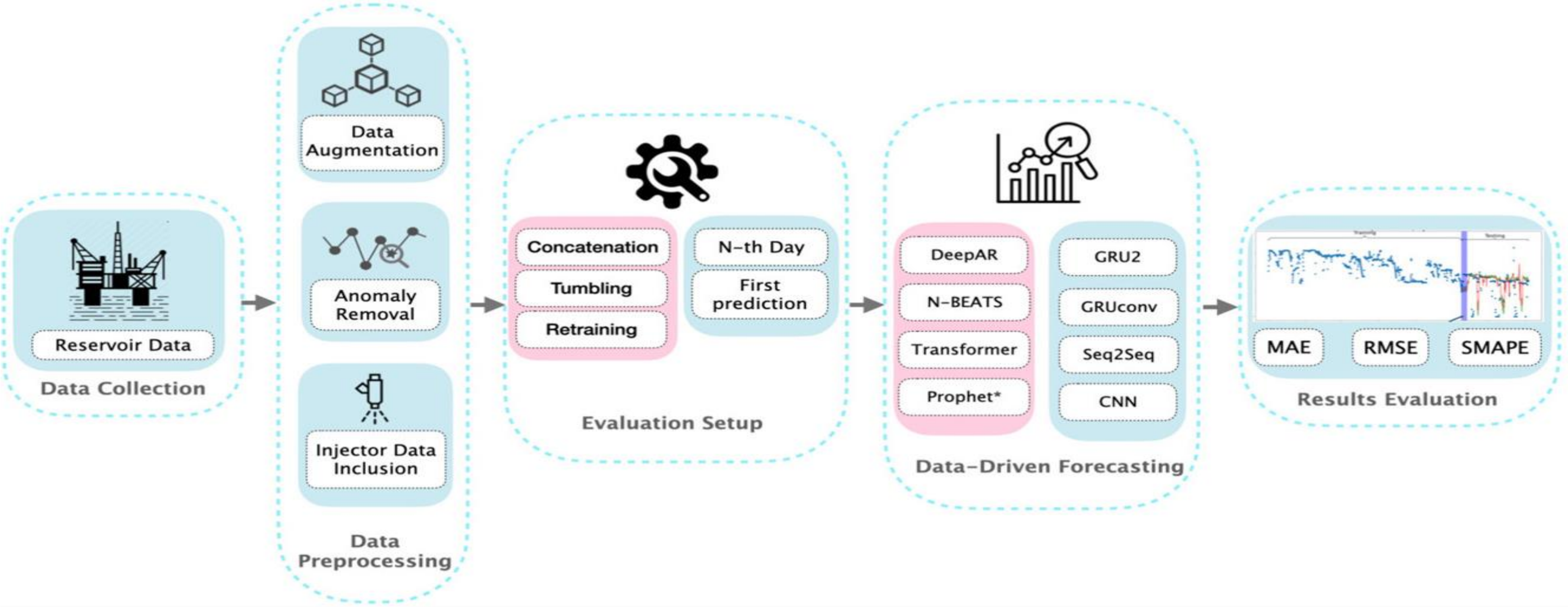
Deep Gated Recurrent Unit Network (DGRU - Deep Learning Neural Networks)



The proposed model can handle the temporal dependencies of complex time-series data at a deep level. It consists of stacks of several layers, where each layer solves part of the task and passes the results to the next layer. Since each layer combines the learned representations of the previous layer and feeds them to a higher layer, better representations of the data can be achieved in the model.

Case Studies

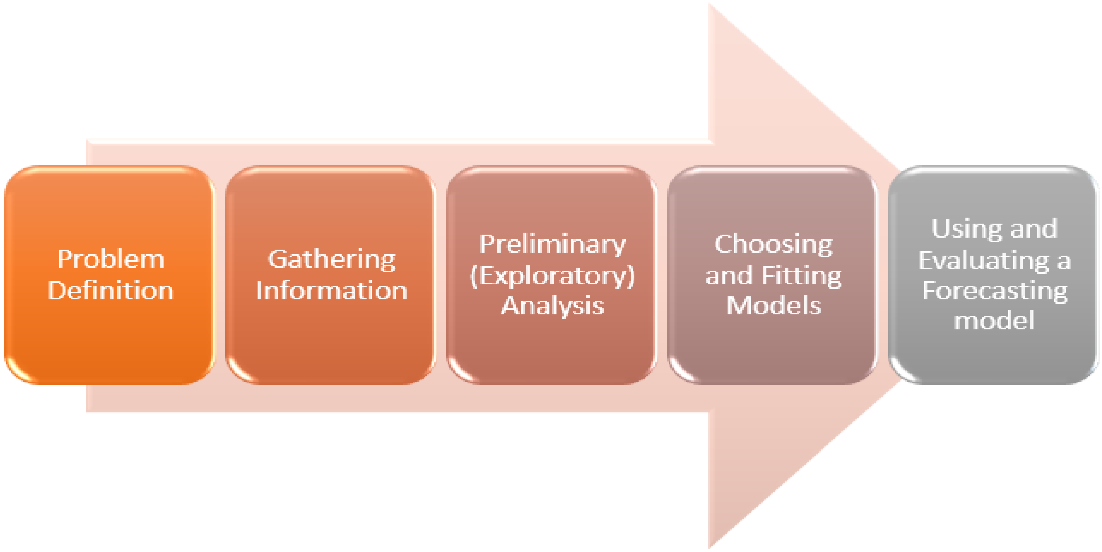
Repeatable and Scalable Methodology for Forecasting



Case Studies

Production Forecasting

Five Basic Steps in a Forecasting Task



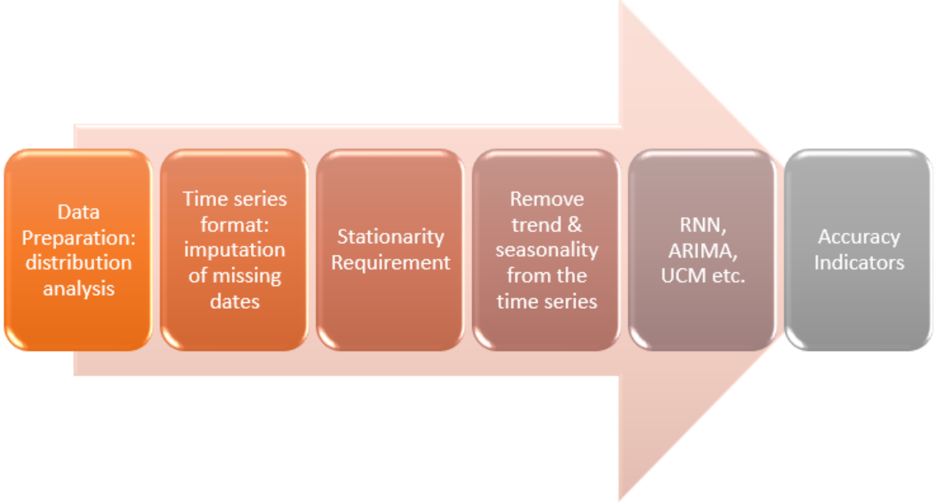
Case Studies

Production Forecasting

Time-Series Data Forecasting

Well Production Workflow

Data-driven analytical workflow to forecast oil/gas production in a well.



Case Studies

Production Forecasting

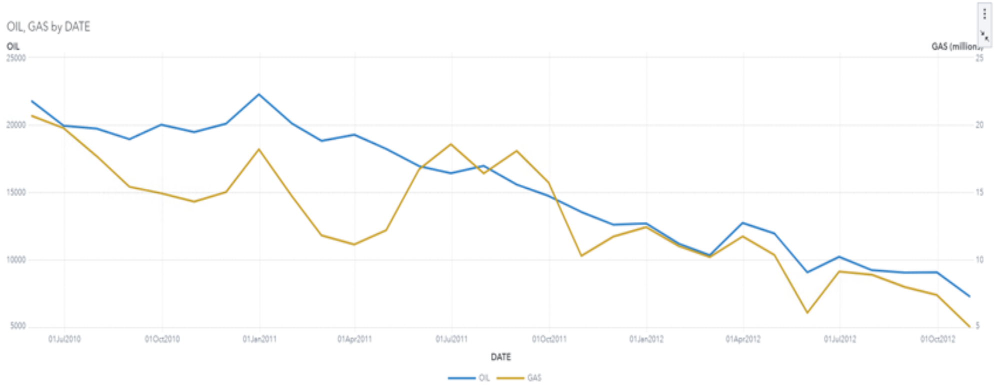
CLUSTER ANALYSIS: WELL PROFILES

Cumulative oil or gas production
Water cut (Percentage determined by water production/liquid production)
B exponent (Decline type curve)
Initial rate of decline
Initial rate of production
Geomechanics and Petrophysical Properties
Geological Parameters
Operational Parameters
Completions Design

Case Studies

Production Forecasting – Let's "stationarize' our temporal data

Oil & Gas Production Decline



DATE	OIL	GAS
31May2010	21760.419361	20678171.017
30Jun2010	19950.990314	19770066.046
31Jul2010	19739.3784	17706084.114
31Aug2010	18953.365184	15434317.195
30Sep2010	20029.094784	14955523.1
31Oct2010	19481.346546	14335004.844

Stationary Time Series	Non-Stationary Time Series
Statistical properties of a stationary time series are independent of the point in time where it is observed.	Statistical properties of a non-stationary time series is a function of time where it is observed.
Mean, variance and other statistics of a stationary time series remains constant. Hence, the conclusions from the analysis of stationary series is reliable.	Mean, variance and other statistics of a non-stationary time series changes with time. Hence, the conclusions from the analysis of a non-stationary series might be misleading.
A stationary time series always reverts to the long-term mean.	A non-stationary time series does not revert to the long term mean.
A stationary time series will not have trends, seasonality, etc.	Presence of trends, seasonality makes a series non-stationary.

Module 10
Time-Series Analysis and Production Forecasting

MODULE 10

This Module introduces a case study to optimize the technical potential of a National Oil Company (NOC.) Technical Potential (TP) forms the basis for future expectations by defining what is achievable and thus highlights the gap between potential performance and what is realized in hydrocarbon production. This knowledge transforms into initiatives that drive the processes for minimizing the gap. Assessment and forecasting TP workflows provide the appropriate tools for NOCs to drive the operator contractors towards better performance targets.

We shall demonstrate a case study to forecast the fluid rates in a brownfield, analyzing historical production data of wells across multiple reservoirs. The proposed methodology is a Deep Learning Long-Short Term Memory architecture.

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