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Development of Neural Model of Gas Processing Plant

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Abstract. Brazil's Ten-Year Energy Expansion Plan (PDE 2034) projects a 97% increase in natural gas processing volumes by 2034. Preventing operational failures is thus critical to avoid off-specification products or disruptions. This study develops a deep neural network using input-output data from a gas processing plant (UPGN) to model dynamic behavior and create a Digital Twin for real-time monitoring. Neural networks provide superior predictive accuracy and faster response times than phenomenological models, which are computationally intensive and unsuitable for continuous applications.

Keywords: Gas Processing Plant, Dynamic Systems, Prediction, Neural Networks, Deep Learning

1 Introduction

The oil and gas sector is adopting Industry 4.0 technologies, including Digital Twins, to enhance operational reliability and efficiency [1]. Brazilian regulations limit gas flaring (ANP Resolution No. 806/2021), while PDE 2034 forecasts a 97% rise in natural gas production, from 68 to 134 million m³/day by 2034. Phenomenological models, based on physicochemical principles, are complex and slow for systems with interdependent nonlinear variables, as in UPGNs [2, 3]. In contrast, deep neural networks offer rapid, accurate modeling of dynamic systems, including transients, making them suitable for real-time Digital Twins [4–6].

This work presents a black-box lumped-parameter model of a UPGN using real data and deep learning (Python, PyTorch) to replicate dynamic behaviors with near-real-time response, enabling comparisons between physical and virtual plants.

2 Description

This study develops and compares deep neural models of a Brazilian UPGN using operational data from approximately 22 months.

2.1 Natural Gas Plant

The UPGN processes dehydrated gas from offshore wells, comprising hydrocarbons (alkanes, cycloalkanes, aromatics) and non-hydrocarbons (N_2, CO_2, H_2O, H_2S). With a capacity of 4.2 million Nm³/day, it features a turbo-expander with booster compressor, Joule-Thomson valve, and demethanizer column for separating methane (C1) from C2+ liquids [2, 3] (Fig. **??**). Preprocessed inlet gas is cooled; NGL bottoms are fractionated downstream (not modeled here). Gas composition varies by well location and time, necessitating adjustments in expansion and column temperature [7, 8]

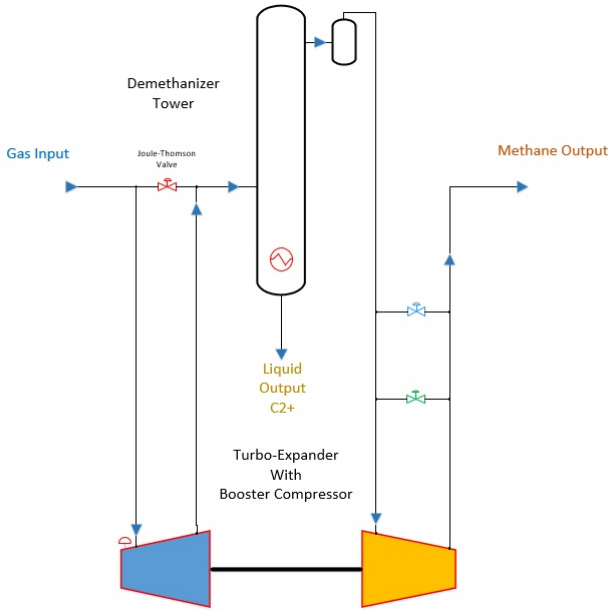


Figure 1. Gas Processing Plant

2.2 Neural Networks and Dynamics

Artificial neural networks (ANNs) are distributed systems of interconnected units computing mathematical functions, with weights adjusted via learning [9]. To model nonlinear autoregressive dynamics, this study uses Long Short-Term Memory (LSTM) [10] and Gated Recurrent Unit (GRU) [11] networks, considering time-series aspects. Architectures follow [12, 13]

2.3 Dataset, Pre-processing and Modelling

Data from March 2015 to December 2016 include 26 inputs and 77 outputs, sampled every minute (668,159 samples per feature), sourced via SCADA and chromatographic analyzers under confidentiality [14]. Preprocessing handled missing values (last valid, inference, or average), excluded non-operational periods, and corrected inconsistencies. Normalization used StandardScaler to stabilize training.

Models process 144-step sequences (2.4 hours) to predict 6 future steps (6 minutes) via LSTM/GRU followed by a dense layer, capturing long-term dependencies. Hyperparameters (layers, hidden size, learning rate, batch size) were optimized with Optuna using MSE [15]; performance evaluated by MAE eq. (1):

$$MAE(y,p) = \frac{1}{N}\sum_{i=1}^{n}|y_i - p_i| \tag{1}$$

Additional metrics follow [16]. Architectures reference [4, 17, 18].

Optimal LSTM parameters: hidden size 128, 1 layer, learning rate 0.000703, batch size 32. Fig. **??** shows temperature TI 001 predictions.

3 Conclusions

Optuna efficiently optimizes hyperparameters for robust multivariate prediction pipelines. LSTM models yield promising results; future work will evaluate GRU architectures.

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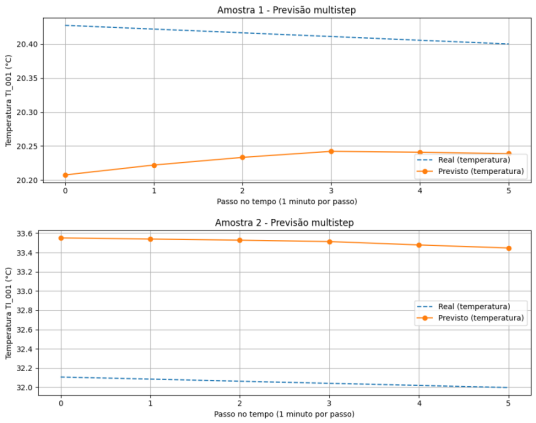


Figure 2. Results for forecasting temperature TI 001 with LSTM Network and Optuna

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