# Enhancing financial decision-making in the oil and gas industry using a deep learning approach

*Abstract*—**The oil and gas industry is characterized by high-value projects with significant financial exposure, requiring precise forecasting of oil barrel prices for effective planning and risk management. Deep Learning models offer a powerful approach to enhancing decision-making by improving predictive accuracy and mitigating financial risks. This research introduces an advanced framework that integrates Deep Learning techniques with traditional statistical models to dynamically select each dataset's most effective predictive approach. Furthermore, it underscores the importance of intuitive visualizations to enhance transparency and confidence in AI-generated forecasts. From a computer science perspective, the study highlights how Deep Learning can strengthen the predictive capabilities of financial decision-support systems. By fostering interdisciplinary collaboration between industry experts and AI specialists, this research demonstrates the strategic value of Deep Learning in managing price volatility, reinforcing resilience in financial planning, and driving innovation in the oil and gas sector.**

*Index Terms*—**financial risk, deep learning, time series, oil and gas, steel.**

## I. Introduction

The advancement of oil exploration technologies in pre-salt reservoirs, such as those in the Gulf of Mexico, Brazil, Guyana, Suriname, the Gulf of Guinea, and West Africa, has driven increasingly complex and high-value projects in the oil and gas industry. However, these investments carry substantial financial risks due to oil price volatility. Studies indicate that fluctuations in this commodity exhibit an asymmetric reaction in stock market returns [1] and directly impact infrastructure and exploration equipment investments. This effect propagates through the supply chain, influencing the cost of strategic inputs such as steel, a key material in subsea system manufacturing. This interdependence highlights the need for advanced financial risk management strategies to enhance predictability and resilience in a dynamic market.

Brent crude oil, a globally strategic product, significantly influences price dynamics across various supply chains. Its volatility drives inflationary pressures and poses key economic growth challenges. Understanding oil price fluctuations and their interdependence with other raw materials is crucial for major suppliers navigating this uncertainty.

Recent research explores deep learning applications for forecasting metal prices in the commodities market, including gold, silver, copper, platinum, palladium, and aluminum. However, due to distinct price behaviors, no single model consistently outperforms all predictions [2]. Other studies analyze the relationship between crude oil prices (WTI and Brent) and precious metals like gold and silver, employing spatial-temporal graph neural networks (ST-GNNs) to capture complex market interactions [3]. These approaches underscore the growing role of AI in financial asset modeling and risk management in commodities.

This study uses a flexible pipe production project as a case study. These pipes, essential for subsea oil and gas extraction in pre-salt environments, have a cost composition detailed in Table I. The primary materials include 25% carbon steel, 13.04% stainless steel, and 35.10% other raw materials such as Aramid Fiber, Nylon, Polyester, Polyethylene, Polypropylene, and PVDF, while transformation costs account for 26.87% of the total.

TABLE I
Cost Composition

| **Product Composition** | **100%** |
|---|---|
| Transformation Cost | 26.87% |
| Carbon Steel | 25.00% |
| Stainless Steel | 13.04% |
| Other Raw Material | 35.10% |

The production of subsea products typically takes 12 to 18 months, with total contract durations reaching 30 to 40 months depending on package composition. Contracts often cover multiple exploration wells, increasing the number of orders and exposing the supply chain to risks like currency fluctuations, commodity price changes, and inflation.

Stock levels are insufficient to meet contract demand, and the gap between price formation and actual steel purchases can range from 6 months to a year. This delay exposes price fluctuations in carbon and stainless steel, which account for about 38% of production costs, with no price adjustments after negotiation. A mitigation plan is essential to address these risks.

Managing financial risks is vital due to long-term contracts and significant investments. Companies need to handle economic uncertainties effectively. With AI and data analytics, the Brazilian oil and gas sector can better manage financial risks, ensuring stability. Deep learning plays a key role in providing accurate predictions that improve cash flow management, risk assessment, and decision-making in this volatile sector.

The application of Deep Learning models, such as LSTM, GRU, and convolutional networks, combined with Value-at-Risk (VaR) techniques, has shown significant advances in volatility forecasting by capturing nonlinear patterns and temporal dependencies, providing more excellent stability in risk estimation [4]. Research in this field has been widely applied in areas such as portfolio risk measurement [5], future currency price forecasting [6], and crude oil market risk

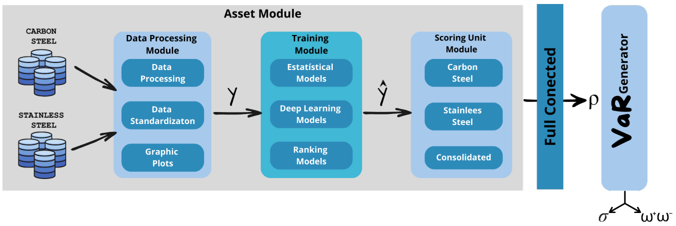


Fig. 1. Model design

analysis [7]. Our study expands this approach by proposing an innovative integration of Deep Learning models with VaR for steel price forecasting, contributing to improved financial risk management in industries that rely on this commodity.

## II. Methodology

In addition to traditional forecasting models, we integrated Deep Learning techniques to enhance the optimization of hyperparameters and improve predictive performance. These methods were applied to time series data for carbon and stainless steel prices, critical in the production systems of subsea products used in oil and gas exploration. This project aims to identify the most effective forecasting model for each dataset through an optimization process, selecting the best model for steel price predictions. This initiative aims to construct a Financial Risk Index based on the volatility of steel prices relative to the contract values offered by an oil exploration company in bids for subsea products. A key challenge in the Brazilian Oil and Gas sector is the mismatch between the procurement prices of raw materials, estimated six months to a year before contract signing, and the final contract value after signing. Often, fluctuations in material costs during this period are not adequately reflected in the updated contract value between the operator and its supplier.

### A. Asset Unit Module

Our methodology involves comparing the performance of traditional models, such as ARIMA, Exponential Smoothing, and Linear Regression, with advanced Deep Learning models, including Transformer, N-HiTS, TiDE, and TCN. This comparison aims to assess the effectiveness of deep learning techniques in predicting steel prices and to determine whether they can capture complex, non-linear patterns that traditional statistical models may miss. Traditional models have limitations in volatility forecasting, while deep learning-based approaches offer advantages to bridge this gap [8]. By contrasting these approaches, we aim to determine whether deep learning models offer superior accuracy, robustness, and generalization capabilities over conventional methods.

As shown in Figure 1, the process begins with collecting carbon and stainless steel datasets from various regions. Data preprocessing includes quantification, handling of missing values, normalization, conducting the Augmented Dickey-Fuller (ADF) test for stationarity, and generating a statistical description of the data, among other tasks.

During the model training phase, we evaluate the deep learning models with 300 epochs to identify the best fitting for each dataset. This evaluation is based on a scoring system, where models are assessed using several performance metrics. The model with the highest aggregate score is then selected as the best predictor for each specific commodity, index, or price.

Once all models have been scored, the next step is to construct the Financial Risk Index, primarily based on the $SMAPE$ results, which will quantify the steel price volatility and its financial impact.

### B. Deep Learning Selection Models

The selection of models to compose the Asset Module was based on the diversity of architectures since the main objective of this research is to evaluate which model presents the most outstanding adherence in capturing the dynamics of the curves, both concerning the type of steel and the production location. An analysis of the results will allow us to verify whether the model architecture significantly influences the identification of risk, enabling, in future studies, a selection of models with technologies like those used in this research, improving the accuracy and efficiency of the integration.

*1) Transformer:* The model architecture used in this study is based on the attention mechanism [9], enabling efficient modeling of long-range dependencies in time series. The Transformer's encoder and decoder layers, built with multi-head attention and feedforward networks, capture relevant patterns across temporal levels. Its ability to model long-term dependencies makes it ideal for commodity price forecasting, while its scalability and parallelism enhance training efficiency.

*2) N-HiTS (Neural Hierarchical Interpolation for Time Series):* The model is designed for time series forecasting, using a hierarchical approach to capture patterns across temporal scales [10]. It decomposes series into trend and seasonality components, processed through specialized blocks with fully connected layers and nonlinear activations. This modular architecture enables accurate interpolation and forecasting across resolutions while regularization and dropout enhance generalization, making N-HiTS effective for complex time series, including commodities.

*3) TiDE (Time-series Dense Encoder):* The model is a modular architecture for time-series forecasting, merging traditional models' simplicity with deep neural networks' expressiveness [11]. It features a dense encoder that captures multivariate relationships while replacing recurrent or attention mechanisms with optimized dense layers, reducing complexity. This enhances efficiency, making TiDE ideal for large-scale, real-time forecasting in volatile commodity markets.

*4) TCN (Temporal Convolutional Network):* The model is a convolutional network-based approach for time series forecasting [12] [13]. It employs one-dimensional causal and dilated convolutions to capture long-term dependencies while preserving causality. Normalization and dropout enhance stability and prevent overfitting. Its parallel architecture enables efficient processing of large datasets, making it well-suited for detecting trends and seasonal patterns in dynamic markets.

### C. VaR Unit Module

Studies on Value at Risk (VaR) are based on the mean-variance model known as the Efficient Frontier Theory, which discusses the tradeoff between risk and returns [14]. The Value at Risk methodology uses standard deviation as a measure of risk, like to the model by Markowitz (1952), making it possible to apply it to credit and liquidity assets. Due to the flexibility VaR offers, the theory can also be applied to studies in different situations, such as investment decisions, portfolio management, hedging, and, in the case of this research, the maximum loss in projects in the Oil and Gas sector. [15], [16]

After choosing the model that best fits the price dynamics of the two types of steel from different origins, the weights will be defined through the distribution of the standard deviation of each price portfolio.

Since the chosen model will define the future commodity price to be used in the project's cash flow, the VaR formula proposed in this research will be the total cost of steel times the error found through the SMAPE metric, as it considers the symmetry between the forecasts and the actual values. For example, a SMAPE of 11.40% represents the average percentage error, considering both overestimates and underestimates, to be 11.40%. This is the prudent value to use when assessing risk in the cash flow. Equation 1 shows the detailed formula.

$$VaR = S_{\text{cost}} * (\omega_1 * X_1)(\omega_2 * X_2)(\omega_3 * X_3)(\omega_4 * X_4) \quad (1)$$

Where $S_{\text{cost}}$ represents the total cost of steel; $\omega$ represents the weighted average by the standard deviation of the historical series, and $X_{\text{n}}$ will be the $SMAPE$ value of each best model defined in the Training Module.

## III. Related Work

In Industry 4.0, adopting advanced deep learning approaches is essential to tackle complex forecasting and monitoring challenges in industrial environments. One example is the real-time monitoring and prediction of material properties in steel manufacturing, ensuring greater efficiency, quality, and waste reduction in the production process [17]. Beyond the factory floor, the concept remains equally relevant in the corporate industrial context, supporting the optimization of financial processes, risk management, and data-driven strategic decision-making.

Machine Learning and Artificial Intelligence are technologies emerging in Corporate Finance and Financial Risk Analysis studies. To improve the efficacy of new studies in the financial field, Deep Learning models have been used for predicting financial disasters [18] and evaluating financial risk in various sectors of the economy: Electric Energy [19], [20] using models capable of projecting consumption; Medicine [21]–[23], tourism, economy, retail, demography, among others [24].

The importance of oil for the economic development of a nation generates a search for coverage against the uncertainty in the price of the commodity. In addition to the effect of the volatility of the price itself, there is also the high variation over time of the raw materials used by suppliers who are part of the first link in the chain of significant oil operators. From more traditional research, techniques in price prediction studies for oil include ARIMA, vector autoregressive models, Monte Carlo Simulation, among others. In the context of nonlinear scenarios, these models tend to perform poorly despite having good efficacy for handling linear and stationary time series.

Contemporary literature has shown a shift in studies on oil pricing from traditional econometric and statistical models to more advanced, nonlinear models with machine learning and Deep Learning techniques to capture the high volatility in oil price curves. This change has brought about some studies by researchers [25]–[27] who now use artificial intelligence and deep learning techniques for oil price projection. This sector is relatively archaic but has been updated through new technologies. This includes explaining price fluctuations during COVID-19 [28] or discussing regional prices, such as in China [29].

Recent research using Deep Learning models, such as Convolutional Neural Networks - CNN [30], Temporal Fusion Transformer - TFT [31], and Recurrent Neural Networks - RNNs using LSTM and GRU [32], [33], have datasets with daily closing values of the oil market in China and the United States. Although published between 2023 and 2024, the datasets are from periods up to 2020 - 2021, which may offer distortions with applications carried out between 2022 and 2024, a post-pandemic period with a cooling in the barrel price.

In addition to presenting an updated dataset, with the final date in December 2023, the correlation of carbon and stainless steel to the fluctuation curve of oil price linked to the geopolitical risk index GPR, our model covers the gap of research done with data from the Brazilian scenario, such as the price of carbon and stainless steel. Additionally, the novel experimentation with the Python DarTS library offers a variety of models, from classics like ARIMA to deep neural networks [34].

## IV. Dataset

The experiments used a steel dataset with two carbon steel and two metallic steel series to assess financial risks in oil and gas projects. These series represent key regions, reflecting steel production and supplier availability.

All the time series are real-world monthly data from agencies monitoring local and global prices. Each dataset underwent pre-processing, addressing seasonality, trends, and missing data.

China dominates carbon steel production as a global distribution hub, while the U.S. is a major stainless steel producer. These factors make both regions ideal for long-term steel price analysis.

Table II shows the composition and formation of the time series used in the experiments.

TABLE II
STEEL DATASET

| Region | Acronym | Observation | Unit | Period |
|---|---|---|---|---|
| China | carbon_chi | 363 | Index | apr/94 - jun/24 |
| Global | carbon_gbl | 363 | Index | apr/94 - jun/24 |
| USA | staninless_usa | 268 | usd/t | mar/02 - jun/24 |
| Global | stainless_gbl | 268 | Index | mar/02 - jun/24 |

After structuring the time series, the Dickey-Fuller (ADF) test was applied to check the stationarity of each variable. It was necessary first to transform the data using logarithms, which showed a high p-value. In the second phase, the technique of log differentiation by a twelve-month moving average was applied to make the series stationary. From this point, the experimental phase began.

Figure 2 presents the time series graph used in this experiment. Although the curves exhibit visually similar patterns, it is essential to emphasize that the choice of purchase location can significantly impact the project's financial return. This is due to regional factors, such as logistical costs, taxes, and price volatility, which can vary considerably from one region to another. For this reason, monitoring both global and regional prices is essential to make more informed and optimized decisions.

### A. Data Processing

The Dickey-Fuller test and statistical analyses were applied to ensure reliable results. This test detects unit roots in time series, determining stationarity by assessing if statistical properties remain constant. It tests the null hypothesis of non-stationarity, rejecting it if the p-value is below 0.05. Non-stationary series require transformations to ensure accurate analysis and forecasting.

Table III presents the statistical description of the Carbon Steel and Stainless Steel datasets, all of them without any transformations and with the Dickey-Fuller test applied, demonstrating that, in all cases, the series are non-stationary, since the P-Value is higher than 0.05. The prices of stainless steel in the USA are in kUSD/t.

TABLE III
STATISTICAL ANALYSIS

| Dataset | Mean | STD | Min | Max | ADF | P-Value |
|---|---|---|---|---|---|---|
| carbon_chi | 148 | 53 | 63 | 326 | -2.6 | 0.09 |
| carbon_gbl | 158 | 60 | 72 | 337 | -2.3 | 0.17 |
| stainless_usa | 5.9 | 1.8 | 2.4 | 11.5 | -2.8 | 0.06 |
| Stainless_gbl | 145 | 34 | 87 | 260 | -2.9 | 0.05 |

To build a financial risk index, it's important to transform the datasets into a form that better reflects the underlying dynamics of price changes. One effective transformation is the calculation of logarithmic returns, which involves applying the natural logarithm to the current price ratio to the previous price as Equation 2. This approach normalizes the data, stabilizes variance, and makes the time series more normally distributed, which is essential for accurate modeling and risk assessment. In the context of steel prices, this transformation captures the relative percentage changes over time, providing a more precise and meaningful analysis of market volatility and risk.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

After applying the logarithmic transformation, the steel histograms align more closely with a Normal Distribution, reducing skewness and kurtosis. The Dickey-Fuller test was then used to assess stationarity by detecting unit roots. As shown in Table IV, all time series yielded a p-value below 0.05, confirming stationarity. Thus, no further transformations were needed before applying deep learning models, ensuring result validity.

TABLE IV
ADF TEST AFTER TRANSFORMATION

| Dataset | STD | ADF | P-Value | Stationarity |
|---|---|---|---|---|
| carbon_chi | 0.0539 | -11.8614 | 0.0000 | Stationary |
| carbon_gbl | 0.0448 | -12.6701 | 0.0000 | Stationary |
| stainless_usa | 0.0438 | -10.4202 | 0.0000 | Stationary |
| stainless_gbl | 0.0374 | -6.1881 | 0.0000 | Stationary |

After processing the time series with transformations, stationarity tests, and normality checks, the next step was defining evaluation metrics. Selecting appropriate metrics ensures a robust comparative analysis, identifying the most effective forecasting approaches. With these metrics established, experimental models can be developed and implemented, providing a solid foundation for result validation and interpretation.

## V. METRICS

The accuracy of each model is measured using seven statistical indices, including RMSE, SMAPE, and MASE, calculated by the library. Additionally, a classification approach consolidates all metrics into a single score, enabling automated model selection. This automation enhances result interpretation, providing a structured and concise decision-making tool.

A highly accurate steel price prediction model helps mitigate financial risks in projects where 38% of costs are concentrated in a single commodity. Future research could integrate these forecasts into cash flow projections, generating new risk and return metrics, such as Net Present Value impact.

Accuracy metrics are crucial, as up to a year can pass between price formation and raw material procurement, exposing companies to price fluctuations. Regional steel supply dependencies further affect costs. After selecting the best models, weights will be assigned based on each time series' local volatility, influencing the financial risk index.

## VI. EXPERIMENT AND ANALYSIS

After defining the models outlined in the methodology chapter, processing the time series of prices for the two types of steel across each country/region, and selecting the best metrics for building the scoring system, we began structuring

Fig. 2. Historical Steel Prices


each model. The first step involved splitting the datasets into training (75%) and testing (25%) sets.

The hyperparameters of the deep learning models were subjected to an optimization process through fine-tuning to maximize the models' performance and effectiveness. For this, the Optuna optimization library was used, a tool that allows for automated and efficient searches in the hyperparameter space. Specific "studies" were created in each model, where different combinations of hyperparameters were tested over ten trials. This process systematically explored parameter configurations such as learning rate, number of layers, number of neurons per layer, and others that influence the model's performance.

All models and their requirements were installed correctly in a virtual environment dedicated to the project using Python 3.12.0. The Visual Studio Code 1.85.1 code editor was employed on the Windows 11 operating system. About hardware, the models were executed on a PC equipped with an ASUS ROG Strix Z590-A motherboard, 64 GB of RAM, an NVIDIA GeForce RTX 4070 Ti Super GPU, and an Intel Core i7-10700K CPU 3.8GHz processor with eight cores.

### A. Hyperparameter Optimization

The hyperparameters of deep learning models were optimized through a fine-tuning process to maximize forecasting performance in time series prediction. The Optuna library enabled an efficient automated search in the hyperparameter space. This study conducted ten trials per model, exploring configurations to identify the best results. A key hyperparameter adjusted in all models was *dropout*, a regularization mechanism that prevents overfitting by randomly deactivating neurons during training, improving generalization.

In the Transformer model, two hyperparameters were optimized to enhance temporal pattern learning. *num_encoder_layers: 1-4* influences the model's ability to extract complex patterns and capture long-term dependencies, while *num_decoder_layers: 1-4* refines these representations into accurate predictions. Optimizing these parameters balanced complexity, learning capacity, and generalization, leading to more robust forecasts.

For the N-HiTS model, optimization focused on three key hyperparameters shaping its hierarchical structure. *num_stacks: 1-4* defines hierarchical stacks, capturing patterns at different temporal scales. *num_blocks: 2-8* controls the number of blocks per stack, affecting model complexity, while *num_layers: 1-4* determines network depth within each block, enhancing the ability to learn nonlinear relationships. Optimizing these parameters fine-tuned the architecture to minimize prediction errors and improve robustness.

In the TiDE model, three additional hyperparameters were optimized alongside *dropout*. *decoder_output_dim: 8-32* influences the dimensionality of the decoder's output, impacting the reconstruction of complex temporal patterns. *hidden_size: 64-128* determines neurons in hidden layers, affecting the model's ability to capture long-term dependencies. *batch_size: 6-32* controls the number of samples processed per gradient update, influencing training stability and convergence speed. Optimizing these hyperparameters with Optuna improved forecasting accuracy and efficiency.

Optimizing the TCN model posed additional challenges due to structural hyperparameter interdependencies. *input_chunk_length* and *output_chunk_length* define input-output window sizes, directly impacting forecasting performance. Additionally, *kernel_size* and *num_filters* must be proportionally adjusted to maintain spatial coherence and avoid distortions in feature extraction. These constraints limited Optuna's optimization to *dropout* and *dilation_base: 1-6*, which determines the receptive field in dilated convolutions, enabling the model to capture patterns at different temporal scales. Balancing these factors was crucial for ensuring robust performance in TCN.

### B. Model Results

The results presented in Table V indicate robust performance from deep learning models compared to more traditional approaches such as linear regression, ARIMA, Exponential Smoothing (E. Smoothing) and Regression Linear (R. Linear) methods. Deep learning-based models like Transformer, TiDE, N-HiTS, and TCN demonstrated greater predictive power, as evidenced by their consistent top-three rankings across the datasets. These results highlight the ability of deep learning models to capture complex and nonlinear patterns in steel price time series, providing more accurate and reliable forecasts.

For each dataset, the results include the performance metrics and the corresponding score for each model. The score is derived from the ranking of models across all metrics that are widely used to assess model accuracy, providing normalized error measures relative to benchmark values. This evaluation framework ensures a comprehensive comparison of model performance across different datasets.

In the first dataset, Carbon Steel China, the TiDE model shows the best overall results, achieving an RMSE of 0.1049 and a total score of 21. The Transformer also stands out, coming in second place with a score of 17, followed closely by N-HiTS with a score of 15. On the other hand, the E. Smoothing model exhibits the worst performance, both in RMSE and the other metrics, with a total score of only 3. This suggests that more sophisticated models like TiDE and Transformer have a higher capacity to capture the volatility of steel prices in China, while traditional methods such as E. Smoothing and linear regression fail to achieve the same level of accuracy.

For the Carbon Steel Global dataset, the Transformer leads with the best overall performance, obtaining a score of 21, reflecting its robust accuracy across all metrics. The TCN model also performs well, scoring 18, indicating its ability to capture global patterns effectively. The N-HiTS model follows closely, scoring 15 points. Once again, the E. Smoothing model has the worst performance, with a score of just 6, showing its limitations in capturing more complex global patterns compared to more advanced deep learning models.

In the third dataset, Carbon Steel USA, the N-HiTS model stands out, scoring 20 points, followed by the Transformer with 17 points. These results suggest that N-HiTS can capture the specific dynamics of the U.S. steel market. The TiDE model, despite leading in the China dataset, achieves a different level of performance in the U.S., coming in third with a score of 15. Once again, the E. Smoothing model shows unsatisfactory performance, scoring only 3 points, demonstrating consistent limitations across all markets analyzed.

The fourth dataset, Stainless Steel Global, reveals a slightly different pattern. Although the TiDE and N-HiTS models led in other datasets, they are closely competing in this dataset, with high scores of 20 and 19, respectively. The TCN model, which also performed well earlier, ranks third with 18 points. However, the E. Smoothing model continues to show the worst results, with a total score of just 1, highlighting its inadequacy in handling the complexity of this global dataset.

Overall, the results indicate that the more sophisticated Deep Learning models, such as TiDE, N-HiTS, and Transformer, consistently outperform across different markets and datasets. These models capture both local and global price variations with higher precision, reflecting the robustness of these techniques for time series forecasting. In contrast, traditional models such as ARIMA, Linear Regression, and E. Smoothing show significantly inferior performance, suggesting adopting more modern approaches for forecasting commodity prices like steel.

In summary, the results suggest that, although all evaluated models have some degree of applicability, Deep Learning methods provide a clear advantage in predicting steel prices. This is due to their ability to handle the complexity and nonlinear patterns present in the data. Therefore, selecting the appropriate model for time series forecasting in commodity markets should prioritize these advanced methods, demonstrating greater accuracy and flexibility in adapting to different scenarios and markets.

TABLE V
STEEL MODEL RESULTS

| Model | RMSE | | SMAPE | | MASE | | Score |
|---|---|---|---|---|---|---|---|
| | Result | Scr | Result | Scr | Result | Scr | |
| Carbon Steel China | | | | | | | |
| TiDE | 0.1049 | 7 | 12.9475 | 7 | 1.1486 | 7 | 21 |
| Transformer | 0.1065 | 6 | 13.4573 | 6 | 1.2045 | 5 | 17 |
| N-HiTS | 0.1105 | 4 | 13.4994 | 5 | 1.2015 | 6 | 15 |
| TCN | 0.1089 | 5 | 13.5775 | 4 | 1.2162 | 4 | 13 |
| ARIMA | 0.1291 | 3 | 16.5175 | 3 | 1.5016 | 3 | 9 |
| R. Linear | 0.1368 | 2 | 16.9006 | 2 | 1.5138 | 2 | 6 |
| E. Smoothing | 0.1472 | 1 | 18.6719 | 1 | 1.7295 | 1 | 3 |
| Carbon Steel Global | | | | | | | |
| Transformer | 0.0968 | 7 | 11.3998 | 7 | 0.9124 | 7 | 21 |
| TCN | 0.0982 | 6 | 11.5001 | 6 | 0.9204 | 6 | 18 |
| N-HiTS | 0.0989 | 5 | 11.5837 | 5 | 0.9273 | 5 | 15 |
| TiDE | 0.1029 | 3 | 11.9180 | 4 | 0.9526 | 4 | 11 |
| E. Smoothing | 0.0996 | 4 | 12.7610 | 3 | 1.0251 | 3 | 10 |
| ARIMA | 0.1051 | 2 | 13.7351 | 2 | 1.1017 | 2 | 6 |
| R. Linear | 0.1392 | 1 | 18.0760 | 1 | 1.4342 | 1 | 3 |
| Stainless Steel USA | | | | | | | |
| N-HiTS | 0.1109 | 6 | 14.2290 | 7 | 0.7782 | 7 | 20 |
| Transformer | 0.1091 | 7 | 14.3358 | 6 | 0.783 | 6 | 19 |
| TiDE | 0.1109 | 5 | 14.5524 | 5 | 0.7953 | 5 | 15 |
| TCN | 0.1111 | 4 | 14.9067 | 4 | 0.815 | 4 | 12 |
| ARIMA | 0.1132 | 1 | 15.2462 | 3 | 0.8338 | 3 | 7 |
| E. Smoothing | 0.1129 | 2 | 15.3198 | 2 | 0.8359 | 2 | 6 |
| R. Linear | 0.1124 | 3 | 15.3756 | 1 | 0.8405 | 1 | 5 |
| Stainless Steel Global | | | | | | | |
| TiDE | 0.1621 | 6 | 21.5331 | 7 | 1.3813 | 7 | 20 |
| N-HiTS | 0.1587 | 7 | 21.6943 | 6 | 1.3854 | 6 | 19 |
| TCN | 0.1662 | 4 | 22.1119 | 5 | 1.4201 | 5 | 14 |
| Transformer | 0.166 | 5 | 22.1278 | 4 | 1.4220 | 4 | 13 |
| R. Linear | 0.1662 | 3 | 22.3903 | 3 | 1.4371 | 3 | 9 |
| ARIMA | 0.1821 | 2 | 25.1154 | 2 | 1.6025 | 2 | 6 |
| E. Smoothing | 0.2319 | 1 | 36.1795 | 1 | 2.1975 | 1 | 3 |

### *C. Risk Financial Index*

After selecting the best model for each steel data set, the Financial Risk Index will be developed, considering the weighting of carbon steel and metallic steel costs in the developed project. In this research, a real-life project was used, which it has the following configurations:

1. Carbon steel purchased from China accounts for 90% of the total cost of this commodity, as all of the steel will be sourced from this country.

2. Stainless steel purchased from the United States represents 90% of the cost of this commodity since all of the steel will be sourced from this country.

3. For global steel prices, both for carbon steel and stainless steel, it was considered that the international price curve

dynamics could impact local price projections by 10%. Therefore, global prices were weighted with a 10% impact.

4. Considering that carbon steel represents 25% of the total project cost, the weighting applied for this commodity will be 59.14% ($\omega_1$) for prices from China and 6.57% ($\omega_2$) for global prices.

5. Considering that stainless steel represents 13.4% of the total project cost, the weighting applied for this commodity will be 30.86% ($\omega_3$) for prices from the United States and 3.43% ($\omega_4$) for global prices.

6. Replacing all the $\omega_n$ and $X_\mathrm{n}$ in the Equation 1, reflecting the importance of each commodity market and kind of steel, the Financial Risk Index for this project is 13.56%.

Using artificial intelligence in the context of high volatility in steel prices can yield significant results in financial outcomes and help mitigate margin losses in large-scale projects. Thus, data-driven decisions become more robust, supported by a clear understanding of market forecasts. This allows organizations to proactively maintain competitiveness, particularly in the Brazilian oil and gas market.

## VII. Discussion

Several studies have explored using Deep Learning techniques as new approaches for forecasting steel and other metal prices, focusing on comparisons that show superior results from these models compared to traditional statistical or regression methods [35]. At the same time, academic literature also examines the application of Deep Learning in building Value at Risk (VaR) models, particularly in the context of currency fluctuations, investment portfolios, and stocks [6], [36], [37].

To assess the applicability and relevance of the Asset Module in sectors beyond the steel market, we tested its generalization potential in forecasting other prices. We applied the module in its entirety, without modifying the models or their architectures, while maintaining the same hyperparameter optimization structure. This approach allowed us to evaluate its adaptability to different contexts without altering the original structure.

To assess the applicability and relevance of the Asset Module beyond the steel market, we tested its generalization potential in predicting other prices. The module was applied exclusively to deep learning models without modifying their architectures or hyperparameter optimization structure. This approach ensured an unbiased evaluation of its adaptability across different contexts.

The results in Table VI confirm that both the total score and the SMAPE metrics remain at levels comparable to those observed when applying the module to steel prices. This reinforces the model's ability to generalize to other sectors, making it a promising alternative for addressing gaps in similar studies across various economic domains.

This study goes beyond these approaches by proposing a model that bridges academic theory with the industrial sector, with a special focus on the financial area of these industries. By integrating artificial intelligence techniques with VaR, a well-established methodology in the financial market, the research aims to demonstrate how collaboration between academic research and industry is crucial for driving profitability, promoting sustainability, and generating value for various stakeholders.

TABLE VI
Commodities Model Results

| Model | RMSE | | SMAPE | | MASE | | Score |
|---|---|---|---|---|---|---|---|
| | Result | Scr | Result | Scr | Result | Scr | |
| Aluminum | | | | | | | |
| TiDE + Opt | 0.1274 | 4 | 16.3500 | 4 | 0.7375 | 4 | 12 |
| Transformer | 0.1301 | 1 | 16.5447 | 3 | 0.7488 | 3 | 7 |
| TCN + Opt | 0.1282 | 2 | 16.7556 | 2 | 0.7559 | 2 | 6 |
| RNN + Opt | 0.1277 | 3 | 17.0334 | 1 | 0.7672 | 1 | 5 |
| Nickel | | | | | | | |
| Transformer | 0.1233 | 4 | 15.3601 | 4 | 0.8041 | 4 | 12 |
| TCN | 0.1250 | 3 | 15.7262 | 3 | 0.8235 | 3 | 9 |
| TiDE + Opt | 0.1259 | 2 | 15.8331 | 2 | 0.8297 | 2 | 6 |
| N-HiTS + Opt | 0.1276 | 1 | 16.1588 | 1 | 0.8477 | 1 | 3 |
| Groundnuts | | | | | | | |
| TCN + Opt | 0.0831 | 4 | 15.1886 | 4 | 0.7667 | 4 | 12 |
| TiDE + Opt | 0.0832 | 3 | 15.5215 | 3 | 0.7836 | 3 | 9 |
| RNN + Opt | 0.0848 | 2 | 16.6437 | 1 | 0.8447 | 1 | 4 |
| Transformer | 0.085 | 1 | 16.0425 | 2 | 0.8142 | 2 | 5 |
| Fishmeal | | | | | | | |
| N-HiTS + Opt | 0.1108 | 2 | 11.8259 | 4 | 0.6664 | 4 | 10 |
| TCN | 0.1107 | 3 | 11.9136 | 3 | 0.6704 | 3 | 9 |
| Transformer | 0.1095 | 4 | 12.0468 | 1 | 0.6764 | 1 | 6 |
| TiDE + Opt | 0.1113 | 1 | 11.9307 | 2 | 0.6718 | 2 | 5 |

The financial risk index, weighted by the Value at Risk (VaR) method, enables robust scenario construction with sensitivity analyses, showcasing the model's performance under varying conditions. A key limitation of this study is restricted access to specific datasets, often available only through subscriptions, which poses challenges for smaller companies. Including these datasets would significantly improve the model's value for forecasting commodity prices. The model, as detailed in Section VI, can be calibrated and adapted to new datasets, including those for other commodities.

By aligning academic knowledge with the practical needs of the sector, innovative solutions are created that enhance competitiveness and efficiency, highlighting the importance of continuous synergy between research and industry for the development of strategic and sustainable solutions in support of corporate decision-making.

## VIII. Conclusion

The results demonstrate the superiority of Deep Learning techniques in predicting steel prices, especially compared to traditional methods such as ARIMA, Linear Regression, and Exponential Smoothing. Models like TiDE, N-HiTS, and Transformer consistently outperform the others regarding error metrics accuracy in local markets, such as the Chinese, USA and global contexts. This high level of accuracy allows for a more reliable assessment of financial risk scenarios, which is essential for decision-making in corporate environments.

Advanced Deep Learning techniques offer a clear advantage in analyzing complex time series, such as commodity prices, due to their ability to capture non-linear patterns and volatile market dynamics. By reducing forecast errors, these models provide more solid support for strategic decision-making, allowing companies to anticipate potential financial risks, such as fluctuations in steel prices, and proactively adjust their operations. This way, organizations can optimize their planning and financial management processes, avoiding significant losses.

In a corporate environment where market volatility and uncertainties are constant, adopting Deep Learning techniques for financial risk analysis is not just an option but a necessity. The improved accuracy of these tools directly contributes to better resource allocation and risk mitigation, providing a significant competitive advantage for companies. Therefore, corporate decision-makers must incorporate these technologies into their risk analysis processes, ensuring greater resilience and adaptability in an increasingly dynamic market.

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