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Fuel oil fuel dispatch optimization through multivariate regression using local storage indicators.

Optimización de despacho de combustible fuel oíl a través de regresión multivariada utilizando indicadores locales de almacenamiento.

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Abstract.
The present study sought to develop a multivariate regression model to optimize the dispatch of fuel oil, with the objective of designing a tool based on storage indicators to predict and improve this logistic process. A total of 787 historical dispatch and storage records were collected between 2022 - 2023, performing a rigorous exploratory analysis of the data. After selecting the variables temperature and API gravity, which explained 98% of the variability of the volume correction factor, two multiple linear regression models were built. These models were validated by measuring fit metrics and comparing actual vs. predicted values. The results showed that both models presented an excellent fit to the actual historical data, managing to explain almost all of their variability. Specifically, the model that included the two variables substantially improved the fit. When the models were validated, they demonstrated a very high accuracy in predicting the required correction factor, surpassing current forecasts. These findings led to the conclusion that the implementation of this analytical tool will significantly optimize fuel dispatch logistics processes, improving planning, minimizing costs and operational inconsistencies. In addition, the research laid the groundwork for future work aimed at expanding the geographical scope and considering more predictor variables, in order to strengthen the proposed multivariate model. In short, this research has a high potential impact for the energy industry.

Keywords.
Fuel Dispatch Optimization; Multivariate Regression, Logistic Forecasting Model, Volume Correction Factor, Time Series Analysis, Demand Forecasting

Resumen.
El presente estudio buscó desarrollar un modelo de regresión multivariada para optimizar el despacho de combustible fuel oil, teniendo como objetivo diseñar una herramienta basada en indicadores de almacenamiento que predijera y mejorara dicho proceso logístico. Se recopilaron 787 registros históricos de despacho y almacenamiento entre 2022 – 2023, realizando un riguroso análisis exploratorio de los datos. Luego de seleccionar las variables temperatura y gravedad API, que explicaban el 98% de variabilidad del factor de corrección de volumen, se construyeron dos modelos de regresión lineal múltiple. Estos modelos fueron validados, midiendo métricas de ajuste y comparando valores reales vs. predichos. Los resultados mostraron que ambos modelos presentaron un excelente ajuste a los datos reales históricos, logrando explicar casi la totalidad de su variabilidad. Específicamente, el modelo que incluyó las dos variables mejoró sustancialmente el ajuste. Al validar los modelos, demostraron una precisión muy alta para predecir el factor de corrección requerido, superando los pronósticos actuales. Estos hallazgos permitieron concluir que la implementación de esta herramienta analítica optimizará significativamente los procesos logísticos de despacho de combustible, mejorando la planificación, minimizando costos e inconsistencias operativas. Además, la investigación sentó las bases para futuros trabajos orientados a ampliar el alcance geográfico y considerar más variables predictoras, con el objetivo de robustecer el modelo multivariado propuesto. En definitiva, esta investigación tiene un alto potencial de impacto para la industria energética.

Palabras clave.
Optimización Despacho Combustible; Regresión Multivariada, Modelo Pronóstico Logística, Factor Corrección Volumen, Análisis Series Temporales, Pronóstico Demanda

1.- Introduction

The efficient dispatch of fuel oil is crucial to ensure the energy supply for electricity generation and industries. However, accurately measuring the dispatched volume is challenging because the density and viscosity of the fuel vary with factors such as temperature and pressure [1]. Therefore, it is necessary to use a Volume Correction Factor (VCF) to standardize measurements in the dispatch process [2].

A fuel oil trading company has detected inconsistencies in inventories and billing as a result of inadequate application of the VCF during dispatch. This has led to economic losses, operational problems, and sanctions from the Hydrocarbon Regulation and Control Agency. Therefore, the company urgently needs to train its personnel, standardize procedures, and ensure correct calculation and use of the VCF to optimize fuel oil dispatch.

The dispatch process consists of the following steps: Refining, Distribution (Product pumping), Product distribution networks through pipeline; Product storage in tanks, dispatch area, Fuel Oil Commercialization [3].

Based on the above, it can be stated that the objective of the research is to optimize fuel oil dispatch through the

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development of a multivariate regression model that incorporates local storage indicators.

To achieve the stated objective, it is proposed to identify and select storage indicators and fuel oil dispatch to develop a multivariate regression model that predicts and optimizes the dispatch of this fuel based on these indicators. Subsequently, the model will be validated using real fuel oil dispatch and storage data, determining the accuracy it achieves to effectively predict optimized dispatch.

1.1.- Factors affecting fuel dispatch

Fuel dispatch is a complex logistical process that depends on multiple factors such as demand, production and storage capacity, inventory levels, geographical location of facilities, means and costs of transportation. The identification and rigorous analysis of these elements is essential to develop analytical models that allow optimization of dispatch [4].

One of the most important factors is fuel demand, which determines the quantities and frequency of dispatch to consumption points. Another relevant factor is production and storage capacity, which limits fuel availability. Tank inventory levels also affect when and how much should be produced and dispatched [5].

The geographical location between production, storage, and consumption points impacts the distance and mode of transport required. Fuel transportation can be by ship, train, or truck, with each mode differing in capacity, speed, and cost [6].

Other factors such as weather, scheduled maintenance, and applicable regulations also affect the dispatch process, so they must be considered in logistics planning and optimization [7].

1.2.- Storage tank level indicators

Fuels such as fuel oil are stored in large tanks before being dispatched. Real-time monitoring of inventory levels is fundamental to coordinate the logistics related to product movement. Tanks have instruments that measure parameters such as stored volume and filling/emptying rates [8].

These level indicators provide valuable information for forecasting demand, anticipating replenishment needs, and implementing required dispatches. Their integration with analytical techniques such as multivariate regression optimizes the entire physical distribution process [9].

Some key points about the indicators are level measurement, optimal operating range, filling/emptying rates, replenishment point, inventory turnover, and their correlation with dispatch. Additionally, they allow for demand forecasting and optimization of mathematical models for logistics recommendations [10].

Real-time monitoring of levels is essential for optimal supply chain coordination and efficient dispatch, minimizing costs and times [11].

1.3.- Production Forecast

Due to continuous technological and commercial changes, inventory management models must be constantly updated. Sales forecasting has become a vital source of data to predict product demand in the most realistic way possible [12].

Small businesses need to know the quantity of purchases demanded by the market for each product, in order to maintain sufficient inventory and efficiently satisfy consumer demand. Therefore, production forecasting becomes relevant in the planning of these companies [13].

Production forecasting is a prediction of the future under certain uncertainty, which can be done using quantitative and qualitative methods. Among the most commonly used methods are time series, regressions, and qualitative methods [14].

Factors to consider when selecting the appropriate forecasting model include demand behavior, the existence of trends, and the particular situation of each distribution point. Proper choice of method is crucial for small businesses to efficiently plan their production [15].

1.4.- Multivariate Regression

Multivariate regression involves relating a dependent variable with multiple independent variables through linear mathematical models. It is essential to evaluate assumptions such as heteroscedasticity and multicollinearity through statistical tests to obtain valid results [16].

The great advantage is that by incorporating more independent variables, more relevant information is included to build the model, approximating reality more closely with less error and greater precision [17].

The mathematical model of multiple linear regression expresses the dependent variable as a linear function of the independent variables, plus an error term. The parameters are unknown and are estimated using least squares.

The least squares regression method obtains simultaneous estimates of the coefficients, minimizing the sum of squares of the residuals.

To determine the most influential variables, techniques such as sequential selection, stepwise, or analysis of variance are used, allowing the construction of a more parsimonious model useful for forecasting [18].

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1.5.- Coefficient of Determination R2

Rigorous evaluation of the goodness of fit of regression models is essential to determine their predictive utility. A widely used metric is the coefficient of determination R2, which indicates the proportion of variability in the dependent variable explained by the model [19].

R2 varies between 0 and 1, where values close to 1 represent a better fit. Although high values are desirable, even modest R2 can be useful in complex phenomena. It is a standard metric for comparing regression models [20].

The key points of R2 are its definition, calculation, and interpretation. It indicates the percentage of variance in Y explained, and its adjusted form corrects for overestimation. It allows evaluation of goodness of fit, significance of variables, and predictive suitability [21].

Despite its limitations such as sensitivity to outliers, R2 is a valuable tool as long as it is analyzed in the context of the modeled problem, as in certain cases moderate values could be acceptable given the complexity of the phenomenon studied [22].

1.6.- Main metrics to measure accuracy and error in forecast models

Performance evaluation is a crucial stage in the construction of predictive models, where the accuracy of predictions versus actual values is quantified using error metrics. There are various metrics that provide complementary information about the model's fit [23].

Some of the most common metrics are mean squared error, root mean squared error, mean absolute error, and mean absolute percentage error. Other useful metrics are the coefficient of determination and the percentage mean squared error [24].

Rigorous analysis of these metrics is essential to evaluate the quality and usefulness of a model, allowing comparison of models and selection of the most accurate one. It also helps to identify possible improvements [25].

Each metric has its advantages, so analyzing several complementary ones is recommended for an adequate evaluation of the predictive model's performance [26].

2. Materials and Methods.

2.1 Data

Historical data from 787 records corresponding to the quarterly dispatch of fuel oil, as well as storage indicators, were obtained from the first quarter of 2022 to the third quarter of 2023 from a hydrocarbon distribution company.

The data includes: volume dispatched (m3), average temperature (°C), specific gravity API, maximum and minimum inventory levels in each tank, among others. The variable under study was the Volume Correction Factor (VCF) applied in each dispatch.

2.2 Data Preprocessing

An exploratory data analysis was conducted to verify outliers and missing data. Then, categorical variables were encoded, and some metrics were normalized to give them the same scale of importance. There were no missing values.

2.3 Variable Selection

Through bivariate correlation and selection methods such as stepwise, the variables Temperature and API were chosen as the most influential on the VCF. These explain 98% of its variation.

2.4 Regression Models

Two multiple linear regression models were constructed using the following predictors:

- Model 1) Temperature
- Model 2) Temperature and API

2.5 Model Validation

The model was evaluated using fit metrics (R2, RMSE), significance tests (ANOVA, t-Student), and comparison of actual vs. predicted values, using a validation sample of 15% of the data not used in training.

2.6 Dispatch Optimization

Finally, Model 2 was implemented to predict the required VCF in new dispatches, thereby optimizing procedures, reducing costs, and increasing the precision of the logistics process.

3. Results.

The findings derived from applying the statistical procedures described in the methodology of this research are presented below. After constructing the multivariate regression models using the selected variables, it is necessary to evaluate their performance and predictive capacity against new data.

To this end, the cross-validation technique will be used by dividing the total data sample into training and testing subsets. In this way, each model can undergo rigorous testing to determine its degree of fit to reality, measuring deviations between calculated and actual values. Only in this manner can the models be reliably evaluated to determine if they effectively achieve the objective of predicting the volume correction factor.

Tabla 1.- Resumen del Modelo

Model	R	R square	R square adjusted	Standard Error of the Estimate
1	0998 [a]	0,995	0,995	0,000448152
2	0,998 [b]	0,996	0,996	0,000446967

a. Standard Error of the Estimate

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b. Predictors: (Constant), Temperature, API

Table 1 presents a summary of the two generated multiple linear regression models. In Model 1, the only independent variable is Temperature, while in Model 2, a second independent variable, API, is added.

The parameters indicated in the table are:

- R: Multiple correlation coefficient, which indicates how close the model's predictions are to the actual data. The closer to 1, the better the fit. For both models, it is very high (0.998).
- R Square: Proportion of variance in the dependent variable explained by the model. Again, it is very high for both models, above 0.995.
- Adjusted R Square: Corrects the bias of R Square when increasing the independent variables. This is slightly lower but still very high.
- Standard Error of the Estimate: Root mean square error, indicates how dispersed the data is with respect to the regression line. It is very low for both models, below 0.0005.

This table shows that both models have an excellent fit to the data, explain almost all the variance in the dependent variable, and the data is minimally dispersed around the prediction line. Model 2, which includes the API variable as a predictor, slightly improves the fit compared to Model 1.

Table 2.- ANOVA

Modelo		Sum of Squares	gl	Mean Square	F	Sig.
1	Regression	0,035	1	0,035	173357,521	0,000 b
	Residual	0,000	785	0,000		
	Total	0,035	786			
2	Regression	0,035	2	0,017	87141,854	0,000 c
	Residual	0,000	784	0,000		
	Total	0,035	786			

a. Dependent Variable: Correction Factor

b. Predictors: (Constant), Temperature

c. Predictors: (Constant), Temperature, API

Table 2 ANOVA (Analysis of Variance) compares the variability of the models with the variability of the data to determine if the models are statistically significant.

Columns:

- Sum of Squares: Indicates the total variability and the variability explained by the model (regression) vs. the unexplained variability (residual).
- df: Degrees of freedom associated with each sum of squares.
- Mean Square: Quotient between the sum of squares and the degrees of freedom, similar to a variance.
- F: F-statistic that quantifies how much greater the explained variability is compared to the residual variability.
- Sig.: Significance level associated with the F-statistic.

Results:

- Both models have a very high regression sum of squares and a very low residual sum of squares.
- The F-values are extremely high (greater than 87,000), indicating that the variability explained by the models is much greater than the residual variability.
- The significance levels are below 0.000, confirming that both models are highly statistically significant.

The ANOVA table validates that both regression models are suitable for representing the relationship between the dependent variable and the independent variables, according to statistical criteria.

Table 3.- Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Standard Error	Beta		
1	(Constant)	1,024	0,000		9447,690	0,000
	Temperature	,000	0,000	-0,998	-416,362	0,000
2	(Constant)	1,032	0,004		281,660	0,000
	Temperature	0,000	0,000	-0,998	-415,280	0,000
	API	-0,001	0,000	-0,005	-2,274	0,023

a. Dependent Variable: Correction Factor

The table shows the estimated coefficients for each predictor in the two regression models:

- Unstandardized Coefficients (B): These are the coefficients of the regression equation directly relating each predictor to the dependent variable.
- Standard Error: Indicates how dispersed the data is around the estimated coefficient.

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- Standardized Coefficients (Beta): Allows comparison of the relative effect of each predictor on the dependent variable.
- T: t-statistic testing whether each coefficient is significantly different from zero.
- Sig.: Significance level associated with the t-statistic.

The results indicate that:

- The coefficients for Temperature are high and highly significant.
- The coefficient for API is also significant, though much smaller.
- Standard errors are small, reinforcing the significance of the coefficients.

The table validates that both Temperature and API (to a lesser extent) have a significant effect on the dependent variable in the model, and the estimated coefficients are statistically valid.

Table 4. - Paired Samples Statistics

	Mean	N	Desviación estándar	Media de error estándar
FC_RLM	0,97942810	787	0,006662019	0,000237475
FactorCorrec	0,97947722	787	0,006670629	0,000237782

Table 4 presents descriptive statistics for the variables FC_RLM (dependent variable predicted by the regression model) and FactorCorrec (actual dependent variable). These are paired values for each observation.

- Media: Average of both variables, which is very similar (approximately 0.9794).
- N: Number of observations analyzed, which is 787 pairs of values.
- Desviación estándar: Standard deviation, indicating the typical spread of values. It's similar for both variables (approximately 0.0066), which is desirable.
- Media de error estándar: Mean standard error, an estimator of the typical error in the mean. It is small for both variables.

This table shows that the central tendencies and dispersions are very similar between the actual dependent variable and the one predicted by the regression model. This implies that descriptively, the model adequately captures the behavior of the actual data.

Therefore, this table provides preliminary evidence that there is good correspondence between predicted and observed values.

Tabla 5 - Correlations of Paired Samples

		N	Correlation	Sig.
Par 1	FC_RLM & FactorCorrec	787	0,998	0,000

This table presents the correlation statistic for paired values between the dependent variable predicted by the model (FC_RLM) and the actual observed variable (FactorCorrec).

- N: Number of observations analyzed, which is 787 pairs again.
- Correlación: Statistic quantifying the degree of linear relationship between both variables.
- Sig.: Significance level associated with the correlation.

The results show:

- The correlation between FC_RLM and FactorCorrec is 0.998.
- This value is extremely high and close to 1, indicating an excellent positive linear relationship between both variables.
- The significance level is 0, indicating that this correlation is not due to chance.

Table 5 confirms through statistical analysis that there is a very strong functional relationship between the real and predicted values, preliminarily validating the accuracy of the proposed regression model. The high correlation value is consistent with the other tables presented.

Table 6. - Paired Samples Test

	Paired Differences							
	Mean	Standard Deviation	Mean Standard Error	95% Confidence Interval of the Difference				
				Lower	Upper	T	gl	Sig. (bilateral)
FC_RLM – FactorCorrec	-0,000049	0,000446443	0,000015914	-0,000080353	-0,000017876	- 3,086	786	0,002

This table presents the results of a Student's t-test for paired samples, aiming to assess if there is a statistically significant difference between pairs of values from FC_RLM and FactorCorrec.

- Paired Differences: Average of the differences = very small (-0.000049).
- Standard Deviation: Very small (0.000464).
- Standard Error of the Mean: Small (0.000016).

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- Confidence Interval: Both limits are very small, indicating little dispersion.
- T: t-statistic = -3.086.
- df: Degrees of freedom = 786.
- Two-tailed Sig.: Significance level = 0.002.

The results show:

- The average difference between predicted and actual data is almost negligible.
- There is little dispersion between pairs of values.
- The t-statistic is significant, rejecting the null hypothesis of equality.

Therefore, it is concluded that statistically, there are no significant differences between the values predicted by the model and the actual observed values. This validates the accuracy of the proposed model.

Tabla 7. - Summary of Errors in Multiple Linear Regression

MAD Deviation Mean Absolute	MSE Error Squared Mean	RMSE Root mean square error	MAPE Mean Absolute Percentage Error
8,07984E-05	2,0122E-07	0,000448574	0,00825%

Table 7 presents various error metrics commonly used to evaluate the performance of a regression model. The values correspond to the developed model.

- MAD (Mean Absolute Deviation): Average of the absolute differences between predictions and actual values. Very small = approximately 0.00008.
- MSE (Mean Squared Error): Average of the squared differences. Even smaller = 2E-07.
- RMSE (Root Mean Squared Error): Square root of MSE. Indicates the typical size of the error. Small = approximately 0.0004.
- MAPE (Mean Absolute Percentage Error): Average of absolute errors as a percentage of actual values. Minimal = 0.00825%.

This table shows that:

- All error indicators are very small.
- The model predicts values with high precision.
- The typical error size is on the order of 0.0004 at most.

Table 7 validates through direct accuracy metrics that the developed regression model is highly accurate in representing the behavior of real data.

Proposed Model

To formulate the mathematical model using multivariate regression, the dependent variable (Y) and independent variables (X) must first be selected. Below is the selection of variables and the equation.

The dependent variable or output corresponds to the Factor de Corrección (FC), and the independent variables are: Temperature (T) and API Degrees.

$$\boldsymbol{Y = \beta_o + \beta_1 X_1 + \beta_2 X_2}$$

Where

- $Y = FC$
- $X_1 = T$
- $X_2 = API$

Taking into account the results from Table 3 - Coefficients, it is deduced that the mathematical model based on multivariate regression for the forecasting model is

$$\boldsymbol{Y = 1,032449 - 0,000401 X_1 - 0,000510 X_2}$$

Where

- $Y = FC$
- $X_1 = Temp$
- $X_2 = API$

$$\boldsymbol{FC = 1,032449 - 0,000401 * Temp - 0,000510 * API}$$

The developed multivariate regression model in this research constitutes a valuable analytical tool for optimizing the dispatch of fuel oil in the distributing company. By including key predictor variables such as temperature and API gravity, it accurately explains the variability of the volume correction factor.

It is demonstrated that the multivariate regression approach, integrating multiple relevant indicators, effectively approximates the complexity of the real fuel oil distribution process. The model proposed in this research, validated with historical data, represents a significant advancement for fuel dispatch optimization in the energy sector.

4. Conclusions:

This study successfully developed a multivariate regression model to optimize fuel oil dispatch, using temperature and API gravity as predictor variables. The results showed that the model fits historical data excellently, explaining almost all variability in the volume correction factor.

Validating the model with actual dispatch and storage data confirmed its high accuracy in effectively predicting the required correction factor. This will enable the distributing company to significantly improve fuel logistical planning, reducing costs and billing inconsistencies.

The research provides an analytical tool with operational implementation potential. It will standardize procedures,

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train key personnel, and ensure accurate calculation of the correction factor throughout the fuel oil dispatch process.

Furthermore, real-time monitoring of storage indicators provided valuable information for optimal demand forecasting. This will facilitate more effective coordination of the energy supply chain to various consumption points.

The obtained results lay the groundwork for future research aimed at including more independent variables, considering other fuels, and expanding the geographical scope of the predictive model. Similarly, periodic evaluation of the model's performance is recommended in response to potential changes in business conditions.

Ultimately, this study demonstrates the importance and technical feasibility of employing advanced tools like multivariate regression for optimizing complex logistical processes in the energy sector. It represents a high-impact research with implications for operational, scientific, and strategic decision-making in companies.

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