Machine Learning Applied to Optimize Fuel Consumption in Amazonian Waterways Military Logistics

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Abstract: The present study is an analysis of the use of Machine Learning tools in favor of river logistics transport in an Amazon jungle area and the impacts on the efficiency of the Logistics Commander's planning, due to a research gap identified through imprecise methods for estimating fuel consumption in logistics trips. In this way, a quantitative mathematical model was developed, using Multiple Linear Regression algorithms (due to its simplicity for operators not specialized in the area) to predict fuel consumption on logistical trips carried out by Vessel's Center of Amazon Military Command (CECMA) vessels, using statistical data found in travel reports. After this, a comparison was made of the model found with the current modus operandi of the complement calculation completed by CECMA. applying a back test to validate the proposed model. The results obtained generated research with an R of 0.935, explaining 87% of the proposed trips. In this context, a software proposal was presented to be developed with an online interface and with the interaction of the two algorithms. Thus, the use of machine learning tools such as MLR, integrated with an AI system with feedback on predictive variables and fuel consumption of logistics missions brings an increase in the efficiency of military logistics planning and reduces costs related to fuel management after missions, contributing to the constant evolution and improvement of Military Doctrine.

1 INTRODUCTION

Military conflicts have undergone several current transformations, as a result of the constant evolution of an increasingly globalized and technological world. A leader's success is associated with their ability to adapt to these continuous changes in processes, people, technologies, and structures, to allow adequate flexibility and speed in decision-making (Horney et al., 2010).

The recent conflict between Russia and Ukraine highlights the importance of these developments in modern warfare. The digital power of belligerent countries is increasingly proving to be a powerful weapon in the conflict (Hirata, 2022).

Added to this is the importance of adequate logistics to enable the effectiveness of all planning carried out. The Logistics function refers to the set of activities that deals with the forecast and provision of all classes necessary for the organizations and supported forces. Its activities are: needs assessment, procurement, and distribution (Brasil, 2018).

Among the logistical nuances within the scope of the Brazilian Army, the river logistics within the scope of the Amazon Military Command was an even greater challenge, due to the characteristics of the modal, mainly procedural deficiencies, personnel and material (Oliveira, 2019).

The execution of this activity in the Western Amazon is the responsibility of the 12th Military Region, through its Directly Subordinate Military Organization, CECMA (Brasil, 2015).

Thus, with the participation of new actors in supporting operations in increasingly volatile and complex environments and the importance of digital power, Machine Learning becomes a viable tool for military operations, due to the technological level this tool achieved (Svenmarck, 2018).

This is because it can update data, through the automation of operational processes and the prediction of behavior, it makes it possible to generate

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greater knowledge and allows, in a more effective way, communication between elements of interest, thus optimizing efficiency. of operations (Davenport, Ronanki, 2018).

Through machine learning, it is possible to systematize automatic learning, based on a historical series of data, by training a large volume of this data. In this way, the system adapts and presents a result with great precision (Elias, 2018).

As a result of the knowledge gap regarding the adoption of Machine Learning in the Brazilian Army, given the importance of this tool nowadays and its use as a possibility to improve planning in logistical missions along the rivers of the Western Amazon carried out, this research was faced with the following question: To what extent would the implementation of machine learning have an impact on improving the planning of commanders responsible for river logistics transport in the Amazon?

In this sense, the objective of this study was to investigate the use of Machine Learning in favor of river logistics transport in an Amazon jungle area, aiming to increase the efficiency of the Logistics Commander's planning in river operations.

2 METHODOLOGY

In this study, a quantitative approach was used. A mathematical model of a quantitative nature was sought to predict fuel consumption on logistical trips carried out by CECMA vessels, using a mathematical model developed from a Multiple Linear Regression.

The instrument used to collect the data was a Data Collection Form. As it is an extensive document, with information of a qualitative and quantitative nature, numerical values referring to the researched variables were extracted, to consolidate the information necessary for the development of the proposed model. In total, data was collected from 100 (one hundred) logistical travel reports carried out in the last eight years (2015-2023).

The one hundred records collected were those that presented the same data pattern. Older reports (prior to 2015) presented a completely different pattern, not useful for the present study. All records were analyzed for possible outliers, to check for inaccuracies or data that may have been entered incorrectly.

The mathematical model was developed based on a Multiple Linear Regression (MLR), considering the following predictor variables for fuel consumption: Vessel Engine Power (HP), Days Sailed (n), Distance Sailed (km), speed (km/h), and load transported (kg) with and against the current. The development and validation of the model were carried out using the proportion of 80% / 20% of the collected records, respectively. Eighty percent will be used to develop the model and the remaining twenty will be used to validate the developed model

Regarding days navigated (one of the predictor variables), CECMA has a protocol for estimating the navigation days needed for each location served, which is based on the estimated speed to ascend and descend the section to be navigated, in addition to the distance. This speed estimate is based on the average performance of each machine, with data recorded in the Operations Center.

According to CECMA travel reports, it is possible to obtain daily round trip data, the average distance sailed, navigation time, type of boarding, number of ferries transported, cargo transported, number of generators and the navigated section (BRASIL, 2022a).

Currently, CECMA has its own model to calculate fuel needs. This is an empirical model, developed based on the observation of trips made and the factors they take into account for the calculation, these being: Distance sailed, speed up and down the river (based on the average speed of navigations already carried out), quantity of generators, estimated mission days (based on old reports, the number of days is estimated) and the consumption of engines and vessels (based on the manufacturer's manual).

The results were submitted to the regression metrics evaluation tools in Machine Learn to evaluate the most accurate model, these being: R, R^2, adjusted R^2, RMSE, and p-value. In the end, a comparison was made of the model found with the current modus operandi of the fuel calculation performed by CECMA. All statistical calculations were performed using JAMOVI v.2.4 software and the significance level was set at 5% (a = 0.05).

3 RESULTS

The first step to build the MLR model was defining the variables. The dependent variable of this study is fuel consumption. Initial independent variables included speed, load, duration, distance, and engine power.

After all the data collected from the 100 logistical travel reports analyzed had been a spreadsheet, the Kolmogorov-Smirnof normality test was performed to test the distribution of the variables. With normality tests, speed and load variables were removed. The other variables followed a normal distribution $p > 0.05$. Table 1 presents the descriptive statistics of the investigated variables.

Table 1: Descriptive Statistics of the predictor variables and fuel spent at 100 Logistical support trips carried out by the Brazilian Army in the Western Amazon Region (12th Military Region), from 2015 to 2023.

Metric	Engine (HP)	Up Load (kg)	Down load (kg)	Up Vel (km/h)	Down Vel (km/h)	Distance (meter)	Days	Consumption (liter)
N	100	100	100	100	100	100	100	100
Medium	505	94317	60193	8.32	14.7	2332	29.1	21369
Variation	144	73375	69465	1.32	2.03	864	12.5	10057
Amplitude	391	471556	314000	7	9	4302	69	61300
Minimum	309	3000	1000	5	10	98	3	1200
Maximum	700	474556	315000	12	19	4400	72	62500

Table 2: Multiple Linear Regression Metrics with the 80 travel samples.

Model	R	R²	R² Adjusted	RMSE	F	gl1	gl2	p
1	0.914	0.836	0.830	4040	129	3	76	< .001

Table 3: Coefficients of variables predicting fuel consumption from logistical support trips carried out by the Brazilian Army in the Western Amazon Region (12th Military Region), from 2015 to 2023.

Predictor	Estimates	Standard error	t	p
Interceptor	- 8361.80	4036.63	-3.73	< .001
Engine Power (HP)	16.85	3.57	4.73	< .001
Distance (km)	2.59	0.90	2.89	0.005
Navigated Days	512.30	55.77	9.19	< .001

$$CONS = 16.85.ENG + 2.59.DIST + 512.30.DAYS - 8361.80 \quad (1)$$

Where: CONS = Fuel Consumption (liter); ENG = Engine Power (HP); DIST = Navigated Distance (km); and DAYS = Days Sailed (days).

The standard deviation of the sample indicates that we have a considerable range in the sample universe, from 144 HP for the engine, 73375 kg for the cargo going up the river, 69465 kg going down, a distance of 864 km, around 12.5 days sailed and a deviation from consumption of almost 10057 thousand liters of diesel oil.

After checking all the information identified as outliers, it was not possible to define the information as discrepant, since these are possible events that may occur during logistical trips. It was also confirmed that there was no data entered erroneously.

However, to better adjust the model, variables that presented a p-value greater than 0.05 were removed, to obtain the most adjusted equation possible.

Therefore, Upstream and Downstream Load and Speed were removed, due to their higher value. Therefore, a second linear regression was run with the independent variables Motor, Distance, and Duration and the dependent variable Consumption.

Multiple Linear Regression (MLR) metrics with the 80 travel samples are presented in Table 2 and the model coefficients in Table 3.

Based on this mathematical model, the verification of the assumptions began to attest to the efficiency of this algorithm. Initially, the Q-Q of residuals was checked, represented in Figure 1, which represents a graphical method to compare two probability distributions, plotting their quantiles against each other.

The distribution of residuals is very close to the straight-line equation presented, presenting linearity between the data distribution.

Continuing with the analysis of the assumptions, the correlation of all independent variables with the dependent variable, which is fuel consumption, represented in Figure 2, was also individually evaluated.

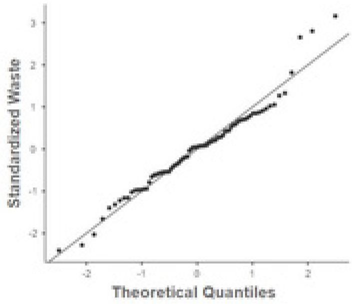

Figure 1: Q-Q Graph of the model to predicting fuel consumption.

Considering the individualized relationship of the variables included in the linear regression equation, it is possible to see that all variables presented a positive correlation, with no null correlations, that is, no significance. This reinforces the relevance of the model obtained as a tool to continue future analyses.

As a last assumption to be analyzed, the possibility of multicollinearity between the variables was assessed, that is, whether there is a relationship between the independent variables as well, considering that the relationships between the dependent variables and the independent variables have already been verified. In summary, the presence of multicollinearity points to a possible insignificance of the variables.

Therefore, the analysis of the variance inflation factor (VIF) is essential to rule out this hypothesis. The VIF is a number and, if its result is 1, it indicates the non-correlation between the independent variables, making the model valid. When this value is greater than 5, the model begins to be considered problematic (Minitab, 2019).

Table 4 represent the MLR collinearity analysis.

Table 4: Collinearity analysis between the MLR independent variables.

Variable	VIF	Tolerance
Engine Power (HP)	1.28	0.783
Distance (km)	2.36	0.424
Navigated Days	2.13	0.470

It can be seen that the values are close to 1, with considerable tolerance to guarantee the fidelity of the developed model.

Furthermore, it is possible to confirm that the mathematical model created with linear regression complied with the validity parameters, in addition to following the assumptions of Operational Research.

Applying the model developed in 20 (twenty) random samples that were not part of the calculation, the MLR model is the best option in 17 (seventeen) of the samples, presenting an average accuracy of 91%, against 64.9% accuracy of the CECMA model.

For this, models were developed, starting with the first 20 (twenty) trips and running the two algorithms in question. After that, the subsequent 20 (twenty) samples were added, and the models were run again, until reaching the total sample with 100 (one hundred) recorded trips. Next, the data is shown in Table 5.

Table 5: Metrics of the Backtest carried out with the 100 (one hundred) logistical support trips carried out by the Brazilian Army in the Western Amazon Region (12th Military Region), in the period from 2015 to 2023.

Model	Sample size	R^2 Adjusted	Accuracy (Model X/Model 5)*100
1	20	0.782	89.8%
2	40	0.805	92.5%
3	60	0.822	94.5%
4	80	0.845	97.1%
5	100	0.870	100%

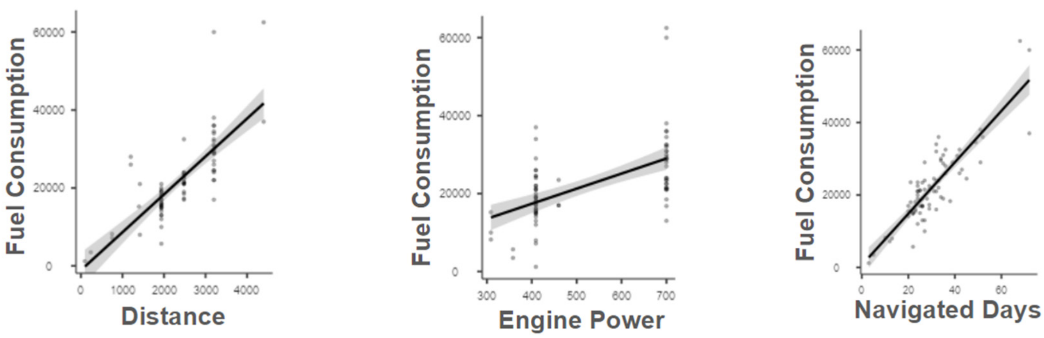

Figure 2: The correlation of all independent variables with the dependent variable.

It can be seen that the larger the sample size, the higher the Adjusted R^2 value, that is, the greater the precision of this model, as shown in Figure 3:

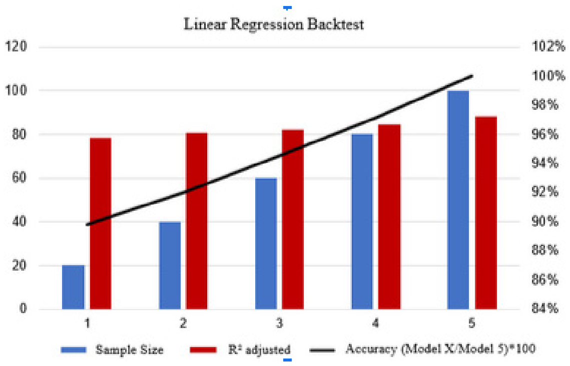

Figure 3: The Linear Regression Backtest.

This information is a condition for understanding the relevance of the model, confirming its validity, and that if it is increasingly fed with more information, its accuracy will be better, bringing greater efficiency to the Commander who uses this tool.

Representing the financial impact generated, the data was presented from an economic perspective, considering the price of diesel quoted at $1.21, as shown in Table 6:

Table 6: Cost metrics for logistics support trips for the 100 samples of logistics support trips according to the metric used.

Model	Actual Cost Avg ($)	Cost Avg ($) with CECMA calculation	Cost Avg ($) with MLR calculation
1	26519.90	30136.25	27243.17
2	25917.17	32547.15	26933.29
3	25314.45	33149.87	26618.33
4	25314.45	30136.25	26574.14
5	25073.36	29533.52	25314.51

According to the data presented, greater precision was identified in the travel cost values calculated with the MLR in relation to the actual cost of the operations analyzed.

Regarding the leftover, when it comes to navigation, vessels' fuel tanks are subject to a greater risk of being contaminated with river water. Furthermore, water condensation in fuel tanks can be a common problem depending on weather conditions (Busnello, 2020).

This contamination changes the characteristics of the fuel, making it possible for these liquids to mix when they are in motion, making it possible to decant them only when the liquids remain in inertia (Oliveira, 2013).

The fuel will undergo natural decantation in order to separate the diesel oil from the water that contaminated it. This decantation has already resulted in a reduction of up to 40% in the initial amount of fuel. After this, the fluid is filtered to remove remaining impurities (Brasil, 2022). Table 7 presents new information, estimating the contamination of 40% of the remaining fuel with water, due to navigation characteristics, as shown below:

Table 7: Assessment of costs and economics of real consumption compared to the current calculation model and the one developed by Machine Learning.

Model	Cost Avg ($)	Quantity of Fuel (liters)	Leftover Fuel (liters)	Waste ($)
Real	25073	20721	0	0
Actual	29533	24407	3686	1784
MLR	25314	20920	721	348

The estimated cost of fuel filtration spent by CECMA in 2022 was approximately R$40,000.00 (forty thousand reais) annually. Considering all the fuel left over from trips this year, approximately 76,000 liters of OD, we have an approximate cost of 0.53 cents per liter for purification. (Brasil, 2022).

According to Oliveira (2013), this fuel filtration process is capable of purifying up to 99% of DO, thus ensuring its use without compromising navigation systems.

In this way, it is clear that making an overestimated fuel calculation for logistical trips is no longer a viable solution, becoming a problem to be measured appropriately. The dichotomy to be considered is not to travel with plenty of OD, however, there must be an adequate safety margin in addition to the fuel needed for eventual unforeseen events and changes in planning.

4 DISCUSSION

In order to validate the presented model, sought to make a parallel with other studies in the area. Searching databases like Scopus and Web of Science, find some really interesting works and researches that appear to have similarities with our study.

The first one is an article where Carmo describes a model to predict fuel consumption in a fleet of ships, using a Machine Learning technique called Boosting.

This tool consists of adjusting an initial model, seeking to improve its efficiency. The main objective is to select the correct results, seeking to improve the results that were not successful, through their correction for subsequent models. It is worth mentioning that this model requires several classifiers with low accuracy, to create a more efficient variable (Carmo, 2021).

Similarities can be identified in the predictor variables used in the previously quoted study and the present research since the variables analyzed by him were: the size of the vessel, the engine power (in HP), the place of origin and destination, departure date and arrival date, the amount of fuel at departure and arrival and the miles traveled. The evaluation of the metrics of the developed model was simpler, with an RMSE of 16.71 and an R^2 of 0.924, against an RMSE of the current model analyzed of 32.99 and an R^2 of 0.892.

At the end of the work, the author did not present a final equation, however, it reinforces the weight that the variables analyzed and the influence that the analysis of the algorithms had on the influence of the fuel.

Another way of verifying the applicability of the model is Backtesting, which consists of an analysis of a series of pre-existing data. This test can identify the behavior of the information, being fundamental in predicting trends in the sample in question (Vezeris et al., 2018).

This model is one of the main ones for outlining strategies in the financial market or logistical analyses, seeking to select the best decisions for analysis (Bailey et al., 2016).

A study made by Takahashi developed a backtest simulating financial return scenarios in 4 (four) strategies adopted over 10 years by 34 different companies. The strategies were linked to the grace period of the titles acquired (Takahashi et al., 2021).

Through the backtesting carried out, it was possible to identify the profitability of each one and analyze its behavior within the historical series. Long-term strategies presented an average annual return of 12.91% against 4.83%, showing the importance of this test to validate developed models.

One of the main products of automated analysis is cost-effectiveness. In our study, the cost of the difference in waste between the models will generate savings of $1,435.00 per trip made (Table 7).

Duarte conducted research to calibrate some inertial instruments, such as gyroscopes, using MLR. The results brought efficiency to the navigation system, improving the reading of results and, consequently, the distribution of signals. All this efficiency results in the reduction of direct and indirect costs (Duarte et al., 2020).

Another interesting work is the analysis focusing on predicting the weather seasons in the region of India, characterized by great unpredictability in natural phenomena, wrote by Shaker and Sureshbabu. This peculiarity contributes to poor resource management and decision-making regarding calamities for farmers in the region. The model developed was able to surpass all existing ones and brought greater economic efficiency to the population since there would be a more efficient allocation of financial amounts (Shaker, Sureshbabu, 2020).

A study that presents great similarities with ours is the research of the fuel consumption of a marine vessel en route also using machine learning, by Hu et al. Due to the characteristics of this type of navigation, the authors considered variables such as wind speed, wave height, fuel recording in real-time every 15 (fifteen) minutes, the vessel's draft, and the direction of the currents (which can be at any sense, not for and against, as they are in rivers). To carry out this analysis, they used Neural Networks and Gaussian Process Regression. Both aim to analyze a set of data, carry out proper training, and predict the data set (Hu et al., 2019).

The metrics evaluated were MSE, RMSE, MAE, and R^2. Through these, the authors compare the differences with different samples, showing their evolution with a broader set of data, such as a backtest.

By way of comparison, this study was able to demonstrate that R^2 evolved significantly, as the amount of data fed into the Machine Learning algorithm database, with a difference from 0.782 to 0.870.

Considering the above study, it can be seen that the author managed to achieve an R^2 greater than 0.98 in both models, the result of a much more detailed historical analysis, with an interval of 15 minutes. However, it is worth remembering that this study has a different aspect, as it concerns maritime navigation, but points to the same direction as the basis of this work.

Another study is Reis' analysis with the linear regression algorithm in a study to identify the attitudinal factors that influence the purchase of remanufactured products. The scope of his work was to develop a relationship between the independent variables, represented by attitudes, and the dependent variable, which is the acquisition of this type of input. The identification of the factors took place through a thorough literature review, as was the case in this study, searching for references that had already identified this phenomenon, in addition to a questionnaire addressed to 287 people, to ratify or rectify the verified notes. To validate the model, the authors used only R, R^2, and adjusted R^2, comparing 7 (seven) models (Reis et al., 2020).

Unlike this work, which presented an R^2 of 0.870 using 3 predictor variables, Reis' models started with just one attribute, with one more attribute being added in the next model, until reaching a model with all 7 (seven) attributes identified.

The highest adjusted R^2 value, in the last model, was 0.642. The author also did not present the correlations between attitudes, the final mathematical model, or any other statistics that would validate the model more efficiently.

In all the works cited above, some points become clear: The need to have a robust and reliable database; the algorithm needs the largest amount of data possible, improving its accuracy as the database is fed; and the metrics evaluated are fundamental to validating the developed model. Without reference to these metrics, it is not possible to say that the product is efficient and suitable for what it proposes; and the search for research in the same field is essential to understand the scope of the study, as well as verify the direction and possible adjustments of the work.

When it comes to the use of machine learning, it was seen as a great opportunity for this research to propose the development of a system in the cloud that can be fed back by users and, at the same time, improve the results obtained in the proposed models.

There are advantages of this type of technology associated with the cloud. Initially, the author points out the strong connection between this type of platform and machine learning, being an effective and economical solution for users of this type of system. The aforementioned author highlights, stating that there is a strong relationship between AI, Big Data, and cloud computing, these being parts of a single technological system (Silva, Bonacelli, Pacheco, 2021).

However, one of the points to be measured is the cost of this technology, as well as its inputs. Although it is difficult to measure, the data uploaded to a cloud system will require a relative storage capacity, information that must be taken into consideration when creating future software (Veldkamp, Chung, 2019).

There are many advantages to this type of system: Access to data in a simplified way, as long as a user has permission to do so; Data control and management, due to easy connectivity; Speed and precision in the decision-making process; and Savings on indirect and direct costs (IBM, 2022).

As already presented in this study, it is clear that the possibilities of machine learning are fundamental in the current context, and it is not acceptable for military managers to neglect its use. Therefore, below, we intend to propose a Machine Learning system for use within the Brazilian Army.

In general, a cloud platform was imagined with a database of all tabulated logistical travel information. This would be the first tab in the system, called "Consolidated Data".

This Big Data would be fed at the end of all missions by the Vessel Commanders. Thus, after filling in this data, it would be updated in the first tab, and MLR would update the mathematical model, recalculating the fuel formula to be planned. It is worth remembering that the greater the volume of information, the greater the accuracy of machine learning. This second tab would be called "Mission Report"

Finally, the third tab of the system, "Planning", would be used by the Operations Center. These users would have the current mathematical model, based on the last trip made, bringing greater efficiency to logistics planning, quickly and economically.

The idea is a system that is constantly fed back, as logistical trips end, in order to consolidate as much data as possible, also improving the efficiency of machine learning.

One of the limitations of this study is the reliability of the data entered in the analyzed reports, with little data entered manually at the end of the day. CECMA reports, although they have a large amount of data, are done manually at the end of the day or even before starting the next trip. This may compromise the reliable release of information, making subsequent double checking impossible.

5 CONCLUSIONS

It can be concluded that the use of machine learning tools such as MLR, integrated into an AI system with feedback on predictive variables and fuel consumption of logistics missions, can increase the efficiency of military logistics planning and reduce costs related to handling. of fuel after missions.

The proposed mathematical model, CONS = 16.85.ENG + 2.59.DIST + 512.30.DAYS - 8361.80 (where: CONS = Fuel Consumption (l); ENG = Engine Power (HP); DIST = Navigated Distance (km); and DAYS = Days Sailed (days) managed to explain 87% of the fuel consumption of military logistical support missions in the Western Amazon.

It is believed that with the implementation of a more robust system, with feedback and an increase in the database, the power of prediction and accuracy of fuel consumption in riverside logistics missions can be increased, generating greater resource savings.

Finally, it is expected that the knowledge presented in this research will be a window of opportunity so that the Army General Staff can begin planning the proposed employment and, consequently, the entire Land Force can reap the possibilities offered by Machine Learning, increasing the efficiency of logistical tasks at all levels, contributing to the constant evolution and improvement of Military Doctrine.

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