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Assessment of NOx Emissions in Combustion Engines for Thermoelectric Power Plants: An Approach with the R and Screen View Programs

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Abstract

Thermal power plants are present in the Brazilian electrical matrix (8% in 2022) and worldwide (61.5% in 2021). Combustion engines are used to drive generators in most thermal power plants, serving as the main sources of atmospheric emissions. This study aims to present a model that allows for the preselection of these engines, identifying those most suitable to the recommended standards for obtaining environmental licenses. Data from twelve engine models were used to evaluate the studied alternatives. Computational resources were utilized through the R program for statistical analysis of the data. Simulations with the Screen View software enabled the investigation of atmospheric dispersion scenarios. The study showed that dispersion presented significant correlations with the following variables: emission rate, with a significance of 0.60, and chimney height, with a significance of −0.57. It was possible to conclude that for wind speeds equal to or greater than the local annual average of 2.1 m/s, a distance of 1800 meters to the community (location of the thermal power plant), a flue gas exit speed of 35 m/s, and the analyzed engine standards and design, engines with a NOx emission rate of up to 3.0 g/kWh showed good dispersion values, below 200 mg/Nm^3 of NOx, the standard required by Brazilian environmental legislation. Thus, only four engine models meet this condition.

Keywords

Atmospheric Emissions, Internal Combustion Engines, Thermal Power Plants

1. Introduction

Compliance with environmental requirements defined by public agencies and private regulatory, monitoring and financing institutions is a matter of survival for enterprises, including thermoelectric plants (Dogan & Tugcu, 2015). CONAMA Resolution 382 (Ministry of Environment of Brazil, 2007) which defines maximum limits for atmospheric emissions from stationary sources and CONAMA Resolution 491 which establishes national air quality standards are examples of legislation in force in Brazil (Ministry of Environment of Brazil, 2018). The Atmospheric Dispersion Study (ADS) is a prerequisite for obtaining environmental licenses and aims to assess the impact of the new enterprise on air quality in communities located within its radius of influence.

The general objective of the research is to identify the best engine option among those evaluated, developing a decision support model using data from scenario simulations. Specifically, to simulate atmospheric dispersions, the following are intended: to analyze engine data specified in technical catalogs, such as emission rate, exhaust gas temperature, engine power, specific fuel consumption and exhaust gas exit velocity; to evaluate the topography of the project; to calculate the distance from the thermoelectric plant to the nearest communities; to examine local environmental legislation and apply current technical standards.

The guiding question of the research is the following: considering the current environmental legislation, is it possible to improve the evaluation of scenarios with combustion engines to achieve greater efficiency in the decision-making process, to meet the air quality standard in communities located within the radius of influence of the future project?

The basic hypothesis is that the development of a methodology for identifying and recognizing emission rate, power and specific fuel consumption patterns will contribute to improving the decision-making process for selecting the best scenario, resulting in projects that comply with current environmental legislation.

In this context, the following secondary hypotheses are considered: regarding atmospheric emission requirements, gas turbines (Brayton cycle) manufactured more than three decades ago can meet the standard defined in current environmental legislation (Clementoni et al., 2014), CONAMA Resolution 491, as long as they undergo retrofitting that includes water injection into the combustion chamber to reduce NOx emissions; and alternative internal combustion engines (Diesel cycle) have post-combustion solutions, treating and filtering combustion gases through a Selective Catalytic Reduction (SCR) system before being released into the atmosphere, in order to comply with the legislation (Ahmadi et al., 2018).

The research considered twelve models of combustion engines from different manufacturers. Two software programs were used: "Screen View" to simulate atmospheric dispersions (Mehdizadeh & Rifai, 2004) and the "R" program with its graphical interface "RStudio" which enabled the statistical treatment of the research data mass (Komperda, 2017).

In thermoelectric plants with combustion engines, these devices are the main sources of pollutant gas emissions. This study was limited to emissions of nitrogen oxides (NOx) because it requires a technological solution with a greater financial impact to ensure an acceptable level of emissions. The solution to control the NOx level also contributes to reducing emissions of other pollutants.

This study was also limited to the twelve combustion engine models presented in **Table 1**, as well as the climatic conditions of the northeastern region of Brazil, where the thermoelectric plant would be installed. However, the methodology presented in this work can be replicated with other engine models and other regions in the world, if the technical operational data of the new engines and the climatic conditions of the new regions are considered in the modeling.

2. Literature Review

According to (Elzalik et al., 2020), thermal power plants are characterized by converting the thermal energy released by the combustion of fossil fuels, biomass, or nuclear fission of uranium into electrical energy. The layout of thermal power plants depends on several factors, such as installed power, type of technology, and fuel used (Favre-Perrod, 2005).

Dedes et al. (2012) confirm that atmospheric emission levels are also associated with the aforementioned factors. According to Nemitallah et al. (2018), current models of gas turbines (Brayton cycle) have embedded combustion technology resulting in low emission levels, meeting the limits established in environmental legislation.

According to Paraschiv et al. (2019), Gaussian-type models are widely used in atmospheric dispersion modeling and are based on a Gaussian distribution of the plume in the vertical and horizontal directions under steady-state conditions, particularly for regulatory purposes, with the same process used with Screen View. Brusca et al. (2016) confirm that the plume distribution is modified according to distance because of turbulent reflection from the earth's surface and mixing height. The plume width is determined by stability classes or the travel time from the source exit to the receptor.

As presented by Alnahdi et al. (2019) Screen View uses a Gaussian plume model, but for a single source. This program can calculate emission concentrations up to 50 km away from the emission source for worst-case scenarios. It is capable of modeling dispersion pointwise, by area, or volumetrically, calculated through numerical and virtual integration of point sources. Atmospheric stability is calculated from Turner stability classes and uses the power law to correct wind speed at heights above 10 m (Holmes & Morawska, 2006).

As addressed by (Zhong et al., 2011), the Screen model code is composed of the Fortran language, which is widely used in scientific computing but is not suitable for graphics development. The Screen was originally designed to calculate ground-level concentrations under the plume centerline in the wind direction. Therefore, Zhong et al. (2011) proposed the use of some tools to extract and take advantage of all Screen's benefits.

According to Racine (2012), the "R" program is a popular open-source tool for statistical analysis and powerful features through its graphical interface "RStudio," which produces diagrams and graphics with high quality. Typically, data mass is the result of research, simulations, modeling, or field or laboratory measurements (Capelli et al., 2013).

Dayal (2015) adds that the "R" program works with data in objects known as datas frames. A data frame is an object with rows and columns, like a matrix. The rows contain different data observations to be studied or measurements from the experiment, called cases. The columns contain values of different variables, called fields. The values in the body of a matrix can only contain numbers, but the values in the body of a data frame can contain numbers and texts.

Issues related to atmospheric dispersion have important applications of linear regression techniques and analysis of variance (ANOVA) for predicting behavior of variables related to the theme (Pongrac et al., 2020). According to Grömping (2015), the "R" program supports a flexible modeling language, using formulas and sharing functionalities with network graph functions.

3. Materials and Methods

3.1. Analyzed Combustion Engines

The engines examined in this study are well-established equipment, with numerous practical application cases, manufactured by international and traditional companies. Table 1 presents the symbols (abbreviations) that will be used throughout this article to represent the studied combustion engines and a brief description of each engine.

Table 1. Combustion engine models.

Symbol	Specifications	Symbol	Specifications
CA	Diesel Cycle—Engine High Speed	CA SCR	Diesel Cycle—Engine High Speed with Catalytic Reduction System
MB	Diesel Cycle—Engine Medium Speed	MB SCR	Diesel Cycle—Engine Medium Speed with Catalytic Reduction System
HE	Diesel Cycle—Engine Medium Speed	HE SCR	Diesel Cycle—Engine Medium Speed with Catalytic Reduction System
WC	Diesel Cycle—Engine Medium Speed	WC SCR	Diesel Cycle—Engine Medium Speed with Catalytic Reduction System
WC T2	Diesel Cycle—Engine Medium Speed	VD	Diesel Cycle—Engine High Speed
TF	Brayton Cycle—Gas Turbine without Water Injection	TF IA	Brayton Cycle—Gas Turbine with Water Injection

3.2. Construction of the Data Set

As presented in the introduction, a data set was structured using some technical and operational parameters, and the results of atmospheric dispersion were obtained through simulations. Table 2 shows the data set with the parameters considered in this research (Ni et al., 2020), namely Tier (classification according to the emission levels established by the United States Environmental Protection

Agency—EPA), Power (MWh), Rotation (rpm), Specific net consumption in liters/MWh, Wind speed (wind speed in m/s), distance until the community (distance in meters from the thermal power plant to the nearest community), Exhaust Temperature (temperature of gases leaving the chimneys in degrees Celsius), Exhaust Velocity (velocity of gases leaving the chimneys in m/s), Emission Rate (emission rate in g/kWh), Chimney Height (meters), and Dispersion (simulation result obtained with Screen in mg/Nm^3) (Turner, 2020).

Table 2. Spreadsheet containing part of the data used in the research (subset of the dataset).

Engines	Tier	Power	Rotation	Consumption	Wind Speed	CommunityDist	ExhaustTemp	SpeedExhau	EmissionRate	ChimHeight	Dispersion	Emis.RateQua	ChimHeightQua	DispersionQua
CA	0	3.25	1.800	254	2.1	1.800	474	35	8.0	15	1.200	Infeasible	Low	Bad
CA	0	3.25	1.800	254	1.5	1.800	474	35	8.0	15	1.150	Infeasible	Low	Bad
CA	0	3.25	1.800	254	3.5	1.800	474	35	8.0	15	1.250	Infeasible	Low	Bad
CA	0	3.25	1.800	254	2.1	1.000	474	35	8.0	25	100	Infeasible	Medium	Good
CA	0	3.25	1.800	254	2.1	1.800	474	35	8.0	25	400	Infeasible	Medium	Bad
CA	0	3.25	1.800	254	2.1	3.000	474	35	8.0	25	1.000	Infeasible	Medium	Bad

3.3. Screen View Software and R Program

In the data set presented above, the dispersion parameter was obtained through simulations using the Screen View software (Espinosa et al., 2021). This program was obtained for free by accessing the developer's website at https://www.weblakes.com/software/freeware/screen-view/. It was necessary to provide the following input parameters to perform the simulations: emission rate, considering the maximum power of the thermal power plant, worst-case scenario, chimney height and diameter, velocity and temperature of gases leaving the chimney, and ambient temperature.

The output data from Screen View were the values of atmospheric dispersion in the communities closest to the project. The results obtained with Screen View and the parameters that make up the different evaluated scenarios were organized in the spreadsheet presented in the previous section, forming the research dataset.

The R program was obtained for free by accessing the developer's page at https://www.r-project.org/, as shown in **Figure 3**. The RStudio graphical platform of the R program was also obtained for free by accessing the address https://posit.co/download/rstudio-desktop/. The processed data set was loaded into the R program, and the RStudio graphical interface (Kronthaler & Zöllner, 2021) was applied, producing statistically significant models and graphics crucial for the research, which are presented in the next section.

These models and graphics were made possible by employing the following "R" analysis packages (Komperda, 2017): "GGally", "readxl", "dplyr", "Hmisc", "corrplot", "PerformanceAnalytics", "ggplot2", "qualityTools", "lattice", "MVar.pt", "ggfortify", "ExpDes", "ape", "psych", "clValid", "cluster", "factoextra", "plotly", "MVA", "ellipse", "HSAUR2", "tools", "maps", "spam", "fields", "CCA", "mvnormtest", "HH", "vegan", "ggpubr", "rpart", "rattle", "rpart.plot", "Cairo", "RColorBrewer", "car", "FactoMineR", "factoextra" (Parsons et al., 2021).

A script, a programming code containing instructions for loading the data set into the R program, instructions on constructing graphs, matrices, tables, indicators, and statistical models, was facilitated through programming language in "R". Additionally, a qualitative evaluation among the variables "chimney height," "dispersion," "emission rate," and the engine models were developed (Chandra & Shang, 2019), considering the parameters indicated in **Table 3**.

Table 3. Qualitative parameters.

Chimney Height (m)	Dispersion (μg/m³) 1 h (Ministry of Environment of Brazil, 2018)	Emission Rate (g/kWh)
High > 30	240 < Bad ≤ 320	Infeasible > 4
15 < Medium ≤ 30	200 < Moderate ≤ 240	3 < Slightly Feasible ≤ 4
Low ≤ 15	Good ≤ 200	Feasiblel ≤ 3

4. Results and Discussion

4.1. Correlation between Variables

Initially, a correlation plot was produced between the variables, as shown in **Figure 1**, where blue coloration indicates positive correlation and red coloration indicates negative correlation (Beunza et al., 2019). The significance levels between the variables are the values shown in the quadrants of the plot. Higher significance levels exhibit more intense coloration, while lower intensity colorations indicate significance less than the intended 0.05 (Kassambara, 2017). It can be observed in **Figure 1** that the dispersion variable is more sensitive to the variables: "EmissionRate" and "ChimHeight" (Chimney Height).

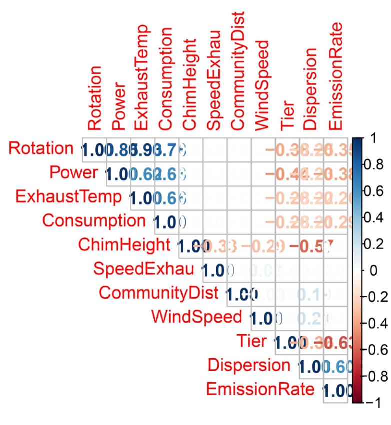

Figure 1. Significance level between variables.

Figure 2 depicts the relationship "Dispersion × Emission Rate" and the engines (Kumar, 2021). According to the data in **Figure 2**, the following engines exhibited technically viable emission rates and dispersion values: HE SCR, MB SCR, TF IA, and WC SCR.

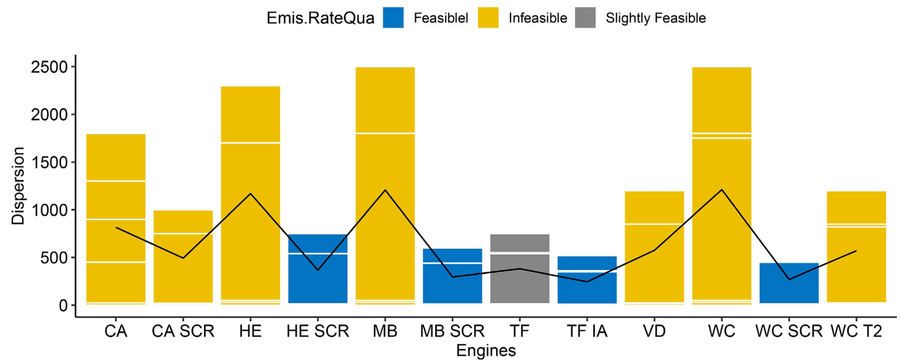

Figure 2. Qualitative Relationship between Dispersion × Emission Rate.

As observed in the graph of **Figure 2**, the blue bars represent the viable engine models considering the variables "Dispersion" and "Emission Rate".

The models with SCR (Kurzydym et al., 2022) and with "IA" (Water Injection System) proved to be viable. It is noticeable that the "Diesel Cycle" engines classified as viable are categorized as "Tier 3", and the gas turbine "Brayton Cycle" has a demineralized water injection system to reduce NOx emissions (Khaliq et al., 2019).

4.2. Linear Regression Models

4.2.1. Regression Model for Dispersion

To quantitatively determine the correlation between the variables that contributed most to minimizing "Dispersion," a selection of correlation tests (Musthafa et al., 2022) was configured, considering all available variables. The summary of the linear regression model is provided in **Table 4**, where it can be noted that the "p-value" was 2.2e−16, with a cutoff line of 0.05 (Macek et al., 2020). Thus, the null hypothesis for the model was rejected, concluding that there is a statistically significant difference between the studied variables.

The "Pr(>|t|)" column represents the p-values, and significance levels are denoted as follows:

- '***' $p < 0.001$.
- '**' $p < 0.01$.
- '*' $p < 0.05$.
- '.' $p < 0.1$.

Summary of the model:

These statistics provide information about the distribution of the residuals, which were the differences between the observed values and the values predicted by the regression model.

Table 4. Summary of the regression model for the atmospheric dispersion parameter.

Predictor Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.070.000	1.527.000	0.700	0.485
Tier	59.390	73.620	0.807	0.421
Power	4.020	8.125	0.495	0.622
Rotation	−6.341	444	−0.014	0.989
Consumption	−7.74	1.992	−0.004	0.997
WindSpeed	47.660	36.070	1.322	0.189
CommunityDist	302.1	57	5.301	4.66e−07***
ExhaustTemp	−648.4	3.776	−0.172	0.864
SpeedExhau	−28.770	5.146	−5.591	1.23e−07***
EmissionRate	149.200	34.240	4.356	2.62e−05***
ChimHeight	−35.290	2.431	−14.513	2.0e−16***

The summary statistics:

- Residual standard error: 283.6 on 133 degrees of freedom.
- Multiple R-squared: 0.7885.
- Adjusted R-squared: 0.7726.
- F-statistic: 49.59 on 10 and 133 DF.
- *p*-value: 2.2e−16.

Adjusting the model and conducting ANOVA tests (Gott et al., 2019) and Shapiro-Wilk normality tests (Ruxton et al., 2015), it was possible to verify that the model is satisfactory, following a normal distribution, with a "*p*-value" of 3.408e−05, as shown in the summary of the model in **Table 5**. In this case, there is evidence to reject the null hypothesis of normality, suggesting that the data significantly deviate from a normal distribution.

Summary.aov (anova1):

Table 5. Summary of the ANOVA test with the model.

Predictor Variable	Estimate	Std. Error	t value	Pr(>|t|)
Tier	1	6725.897	6725.897	68.224
Power	1	9519.925	9519.925	96.565
Rotation	1	567.424	567.424	5.756
Consumption	1	44.992	44.992	0.456
WindSpeed	1	2358.908	2358.908	23.927
CommunityDist	1	2065.920	2065.920	20.956
ExhaustTemp	1	61	61	0.001
EmissionRate	1	1587.284	1587.284	16.101
ChimHeight	1	14495.321	14495.321	147.033
Residuals	134	13210.494	98.586	

The construction of the linear model using the 'lm' function generated the model presented in **Figure 3** (Real et al., 2022), where the predicted dispersion values by the model and the actual values are shown. **Figure 4** displays the distribution of residuals, with no noticeable clustering in their distribution. Both graphs demonstrate normality in the linear regression model (Cheshmehzangi et al., 2022).

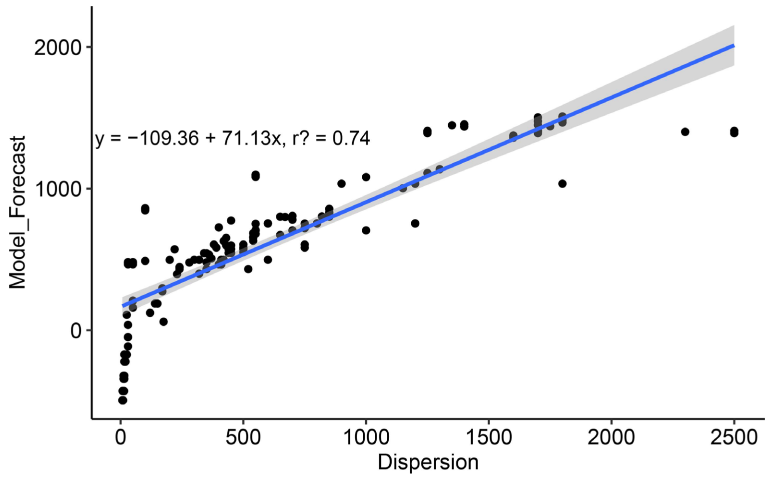

Figure 3. Regression models for dispersion.

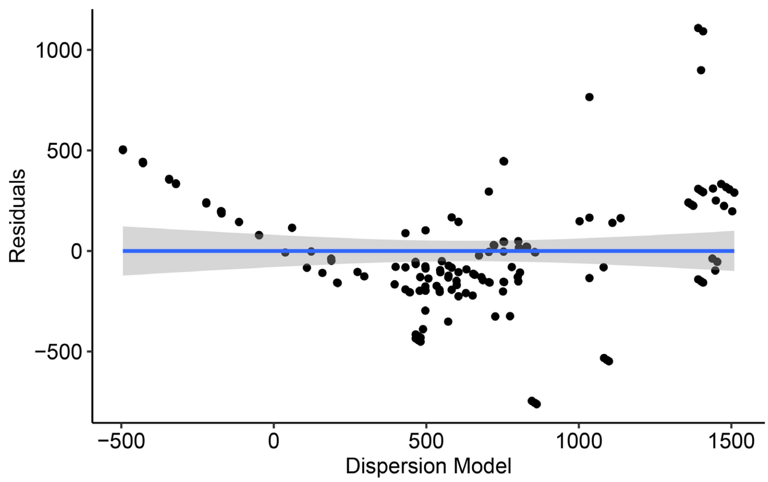

Figure 4. Residual distribution for the dispersion regression model.

4.2.2. Multiple Regression Manova

The research used MANOVA test to examine the relationship between multiple response variables and predictors. Pillai's trace statistic helped identify important differences in mean vectors, revealing that the variables "EmissionRate", "ChimHeight" and "Dispersion" are strongly correlated. An individual analysis was also performed to check the normality of the data.

The hypothesis tests conducted by Pillai, Wilks and Hotelling-Lawley (Mello et al., 2018), as presented in **Tables 6-8** respectively revealed the presence of systematic differences and highly significant responses for the variables "Emission Rate", "Chimney Height" and "Dispersion" as follows.

The summary of Pillai's test is presented in Table 6.

Table 6. Summary of Pillai's correlation.

Predictor Variable	Df	Pillai	Approx F	Num Df	Den Df	Pr(>F)
EmissionRate	1	0.94282	274.118	8	133	<2.2e−16***
ChimHeight	1	0.19420	4.007	8	133	0.0002753***
Dispersion	1	0.32809	8.118	8	133	6.808e−09***
Residuals	140					

The summary of the Wilks test is presented in Table 7.

Table 7. Summary of the Wilks' correlation.

Predictor Variable	Df	Pillai	Approx F	Num Df	Den Df	Pr(>F)
EmissionRate	1	0.05718	274.118	8	133	<2.2e−16***
ChimHeight	1	0.80580	4.007	8	133	0.0002753***
Dispersion	1	0.67191	8.118	8	133	6.808e−09***
Residuals	140					

The summary of Hotelling-Lawley test is presented in Table 8.

Table 8. Summary of the Hotelling-Lawley correlation.

Predictor Variable	Df	Pillai	Approx F	Num Df	Den Df	Pr(>F)
EmissionRate	1	164.883	274.118	8	133	<2.2e−16***
ChimHeight	1	0.2410	4.007	8	133	0.0002753***
Dispersion	1	0.4883	8.118	8	133	6.808e−09***
Residuals	140					

The principal component analysis reduced the number of factors that satisfactorily predicted the studied model. In the results presented below, it is noted that the first five factors were responsible for approximately 92% of the variances, as shown in the standardized data presented in Figure 5.

To assess the quality of the variables composing the principal components, the "COS2" resource was utilized. A high "COS2" value indicates a good representation of the variable in the principal components (PCs). The variables demonstrating the best quality in the composition of "Dim.1" were "Power", "Rotation", "Consumption" and "ExhaustTem" (Exhaust Gas Temperature), as shown in Figure 6 (Burren & Pietsch, 2021).

According to Figure 6, the contribution of the variables "Power", "Rotation", "Consumption" and "ExhaustTem" to the best quality in the components of

"Dim.1" have been justified by their relationship with the amount of fuel burned in the process of generating electrical energy through thermoelectric plants, meaning that the greater the power produced, requires greater quantit of burning fuel (Consumption) to keep the rotation of engines resulting in higher exhaust gas temperature (ExhaustTem) and, consequently, a higher Dispersion value.

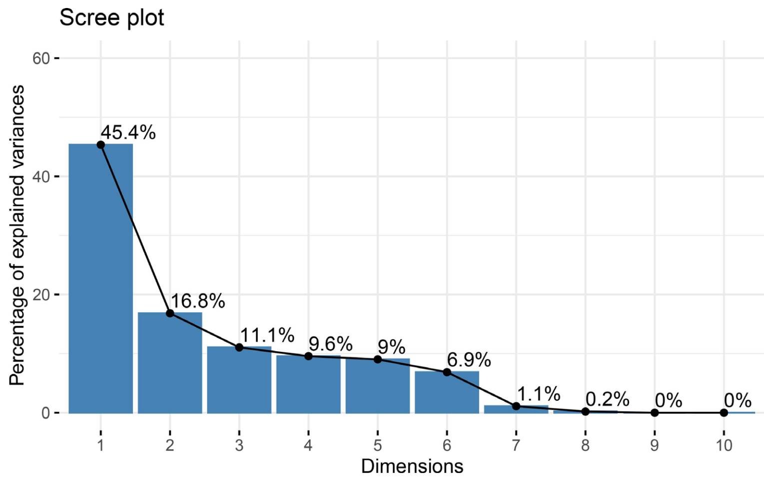

Figure 5. Contribution of factors.

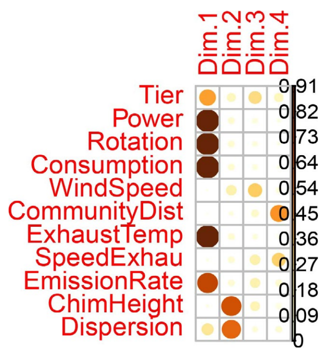

Figure 6. Quality of variables COS2.

In "Dim.2," it was observed that the primary contribution to the composition of the PCs is from the variable "ChimHeight" (Chimney Height) which was strongly correlated with "Dispersion." In "Dim.3," "WindSpeed" and "Tier" represents the mains contributions to the composition of the PCs. Finally, in "Dim.4," the variable "CommunityDist", distance until the community, was the main contribution to the PCs.

The correlations between the variables and the engines models are displayed in **Figure 7**, indicating interaction with "Dispersion" (Burren & Pietsch, 2021).

The joint analysis of the correlation between the contribution of PCs, Engines and Dispersion, as presented in **Figure 7**, showed that MB SCR, HE SCR, WC SCR, and TF IA engines exhibited the best results, being feasible from the perspective of emissions and atmospheric dispersion.

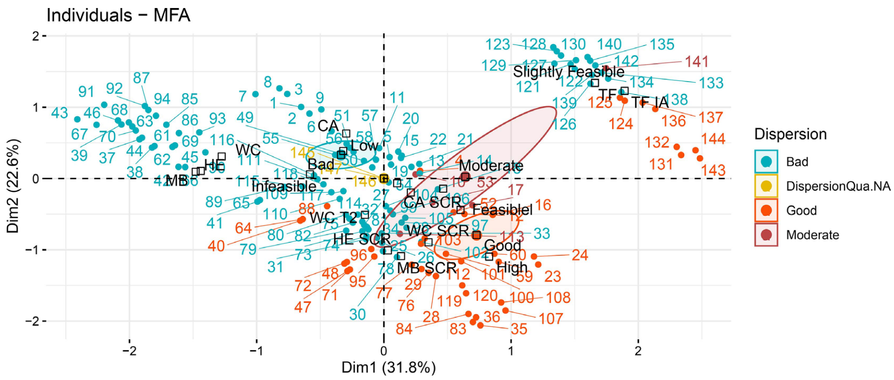

Figure 7. Correlation between the contribution of PCs, Engines, and Dispersion.

5. Conclusion

This paper presents a model for selecting combustion engines in thermoelectric projects prior to the atmospheric dispersion study (ADS). This selection optimizes time and costs, avoiding rework and delays, since these engines are the main sources of pollutant emissions. The research fills a gap in the literature on selection models specific to this context. A project with twelve types of engines was used as the basis for the analysis, employing free software tools, such as Screen View and RStudio, for dispersion modeling and data processing.

The analysis of emission data, through the resources provided by the "R" program associated with Screen View, demonstrated that the best solutions, from the perspective of atmospheric emissions and disperson, considering the analyzed combustion engine models, were WC with SCR system, MB with SCR, HE with SCR and TF IA with injection water system. The WC SCR, MB SCR and HE SCR models, all with Tier 3 classification.

The Gas turbine (TF model) without injection water system was the only "Slightly Feasible" engine solution with atmospheric dispersion value near of limit definided in Resolution CONAMA 491, considering the chimney height of 25 meters. The other engine models only presented viable results with a chimney height of at least 45 meters, being rejected because in the case of alternative combustion engines, the individual power is small, requiring dozens or hundreds of engines to reach the maximum power of the thermoelectric plant and chimneys need to be individualized.

The conventional alternative engine models, without Tier classification or lower than Tier 2, had "Bad" results. The Gas turbine model (Brayton cycle) "TF," without the water injection system for NOx reduction, also had "Bad" results. However, the turbine model considered in this study is from the 1980s, lacking updated technology for reducing atmospheric emissions, which justifies the "Bad" results.

The results showed that "Dispersion" is strongly impacted by the variable "Emission Rate" and "Chimney Height", so any solution to reduce the level of Dispersion should consider these two variables. The best solutions must consider the technology embedded in the engines, mainly those related to the combustion process, to minimize the impacts of emissions at the source.

The average annual wind speed in the studied region was 2.1 m/s, a value that contributed to the "Good" results for the Dispersion variable. Wind speed values above 3.0 m/s require a "medium" or "high" chimney height (**Table 2**), even for engines with a "feasible" emission rate. The correlation between these variables and the other was presented in **Figure 1**, **Figure 2** and **Figure 6**.

The main components analysis demonstrated that the variables with the best quality in the composition of "Dim.1" were "Power", "Rotation", "Consumption" and "ExhaustTemp" (Exhaust Gas Temperature), as shown in **Figure 7**. It was justified by their relationship with the amount of fuel burned when the power was greater, requiring greater quantit of fuel (Consumption) to keep the rotation of engines resulting in higher exhaust gas temperature (ExhaustTem) and, consequently, a higher Dispersion value.

The data analyzed also showed that for a "Wind Speed" of 2.1 m/s, average annual in the studied region, "Distance to Community" of 1800 meters, "Exhaust Gas Velocity" of 35 m/s, characteristic of the analyzed engines, alternative combustion engines with NOx emission rate of up to 3.0 g/kWh presented the best results for atmospheric "Dispersion." This emission rate value can be achieved by reciprocating internal combustion engines with "Tier 3" certification.

Tier 3 engines have SCR system, a feature that impacts the initial project cost by approximately 8% to 10%. This system also impacts operational costs, due to the need for periodic replacement of catalysts and the use of AdBlue (Silva et al., 2017). Thus, it is important to assess the financial impacts through Technical and Economic Feasibility Studies (TEFS) of the project.

This study was limited to NOx emissions as they are the most challenging atmospheric pollutants in thermoelectric projects when it comes to Diesel cycle and Brayton cycle combustion engines. Technological solutions to meet NOx emission requirements help to meet other atmospheric pollutants.

Therefore, the model proposed in this research contributed to the pre-selection of combustion engines in a thermoelectric project, according to the analysis of emissions and atmospheric dispersion. This model did not intend to replace the definitive atmospheric dispersion study that must be provided to the environmental agency to obtain the Preliminary License and Installation License for the new project but contributed to cost reduction and time for the elaboration of ADS. Finally, although this study was limited to thermoelectric projects, it can be replicated and extrapolated to other industrial sectors.

Data Availability

Data will be made available on request.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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