

Energy Consumption Optimization in Industrial Production Based on Calculus Models: In Cars Production Industry

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Abstract: Environmental degradation is one of the most pressing and alarming issues of the contemporary age. Of various causes of pollution, the automotive manufacturing sector is one major contributor to environmental degradation. More specifically, automobile manufacturing involves a large percentage of total pollution. This research is concerned with the analysis of Ferrari's vehicle production environmental impact between 1990 and 2023. It analyzes the overall emissions of six key pollutants: carbon dioxide, nitrogen oxides, particulate matter, sulfur oxides, volatile organic compounds, and carbon monoxide. From the analysis of the emission patterns of these pollutants, this paper is interested in knowing the environmental impact of high-performance car production. To predict future effects, the study uses logistic regression modeling to predict possible variations in pollution levels for the subsequent years. It is able to determine trends and possible stabilization and gain insight into sustainable development for the automobile industry while highlighting reducing environmental damage.

Keywords: Car manufacture, pollution, environmental damage.

1. Introduction

Confronting the emerging threat of global warming, carbon footprint minimization and energy consumption for maximum output have been the highest-priority tasks of all the departments, especially automobile manufacturing [1]. As a high-technology operation involving multiple technicalities, automobile production is nature-oriented for destruction [2]. Therefore, scientific mathematical modeling to minimize wastage in the production process and optimal utilization of energy is necessary in the sustainable development process. Through greater efficiency and reduced consumption of resources, the automobile industry can be a leading player in solving the problems of the environment and providing people with a greener future.

Car production has a lot of processes, including stamping, welding, painting, assembly, testing, etc. In all aspects of automobile production, volatile organic compounds (VOCs) are found in large amounts in processes [3]. These materials will be released into the air, causing significant air pollution and damaging health, and furthermore increasing the carbon emissions. At the same time, the polluted water and other materials in the manufacturing process contain heavy metals and harmful chemicals [4]. These things will be released in the rivers and the air, causing serious water pollution. Thus, to reduce damage to the environment, car manufacturing will be an effective way to protect the environment.

In order to effectively suppress energy consumption and pollution in the automobile production industry, it is essential to create a scientific rational energy model [5]. Dependent on models grounded on a high calculus basis, this present research attempts to effectively analyze the mode of energy consumption during the process of various stages of manufacturing, i.e., stamping, welding, painting, and assembling [6]. By means of extremal analysis and differentiation, one can define an equilibrium point among production parameters under crisis-temperature, pressure, and production levels-and energy expenditure [7]. For instance, in welding and stamping, differential analysis can identify center variables influencing energy expenditure, and production rate variation in devices as well as the temperature level can be applied for the minimization of energy loss [8]. With this, statistical methods like regression analysis can also be used in trying to test the independent influence of different production parameters and ascertain quantitative relationships between different factors. With this, the benefit of having some minimum rate of energy consumption while at the same time having maximum output is assured. With this, calculus and statistics will allow dynamic measurement and real-time optimization of production [9].

By monitoring the patterns of energy consumption and coordinating production inputs, firms can minimize enormous levels of energy wastage and pollution. For instance, web technology is employed in monitoring pressure and temperature fluctuations in order to control the operation of equipment to the point where energy usage is optimal regardless of the production level. Furthermore, prediction systems based on historical data can also make the energy efficiency even better by identifying potential inefficiencies and preventing them from happening [10].

This paper is a shining light to the change of the car manufacturing industry into a more green and sustainable one. Through the incorporation of mathematical modeling and advanced statistical methods, it gives a complete framework for the minimization of wastage of energy and environmental impact of automobile manufacture. Through acceptance of these interventions, the sector is able to transition towards a sustainable future in harmony with the needs of production and ecological sustainability.

2. Methods

2.1. Data description

The database is available on the Ferrari website. It was reported in the sustainability report from the Ferrari company. The dataset contains the index change in six main air pollutants from 1990 to 2023 in the .CVS format and does not have any missing values. The emission values of the data are standardized to 100 based on 1990, and the emission index for subsequent years indicates the relative change relative to 1990. The data contained 204 sets of data for six different pollutants from 1990 to 2023.

2.2. Variable selection

This article uses the production dataset from Ferrari sustainable report, including emissions of key pollutants such as ammonia, nitrogen oxides (NO₂), non-methane volatile organic compounds (VOCs), particulate matter (PM₁₀ and PM_{2.5}), and sulfur dioxide. Table 1 below shows the pollutants analyzed in this study along with their definitions and the years of data available.

Table 1: Variable description

Pollutant	Definition of the Pollutant
Ammonia	A nitrogenous compound, often released during combustion and various industrial processes in manufacturing.

Table 1: (continued).

Nitrogen Oxides (NO ₂)	A group of gases contributing to air pollution and acid rain, produced by combustion in vehicles and industrial processes.
Non-Methane VOCs	Volatile Organic Compounds that contribute to smog and are released from various stages of the automobile production process.
Particulate Matter (PM ₁₀)	Tiny particles suspended in the air that can be inhaled, originating from manufacturing processes like welding and painting.
Particulate Matter (PM _{2.5})	Finer particles that pose a greater health risk due to their ability to penetrate deep into the lungs.
Sulfur Dioxide (SO ₂)	A gas released from industrial processes, particularly from high-temperature combustion in the production of certain materials.

2.3. Method introduction

This article employs SPSS to do logistic regression to explore the relationship between energy consumption and environmental factors in automobile manufacturing industry.

The estimation of the model was done using SPSS, with the Wald tests and likelihood ratio test having been used to examine for the significance of every coefficient. Model fit had also been tested based on measures like the Hosmer-Lemeshow goodness-of-fit test and area under the Receiver Operating Characteristic curve (ROC) curve (AUC). The best model was chosen depending on how it predicted and how easy it was to interpret.

Through this logistic regression method, the research seeks to measure the influence of different production factors on energy use and emission rates of pollutants and hence establish a statistical basis for optimizing automobile manufacturing processes.

3. Results and discussion

3.1. Descriptive analysis

The figure 1 is the Cluster diagram of the emission amount of Ammonia (NH₃) from 1990 to 2022. Ammonia emissions overall decreased but still rose at times.

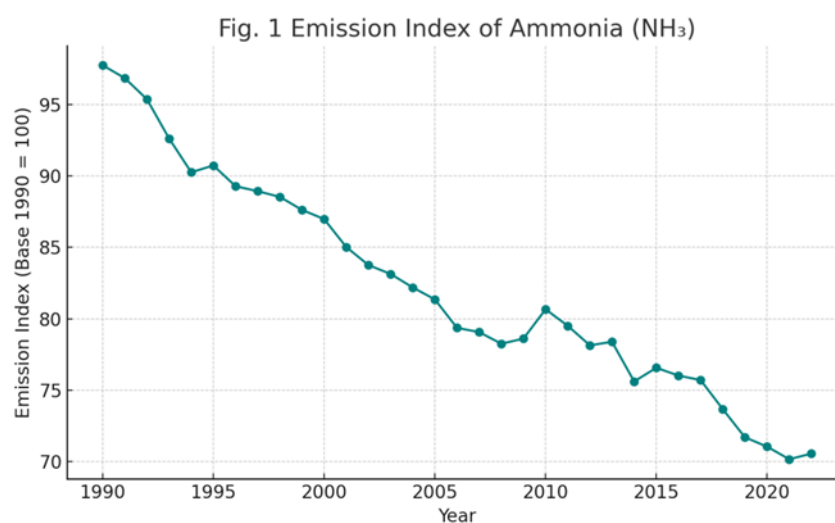


Figure 1: Emission index of Ammonia

The figure 2 is the Cluster diagram of the emission amount of Nitrogen Oxides (NO₂) from 1990 to 2022. Nitrogen Oxides' emissions have been in a state of decline, although there are small fluctuations, but the overall impact is minimal.

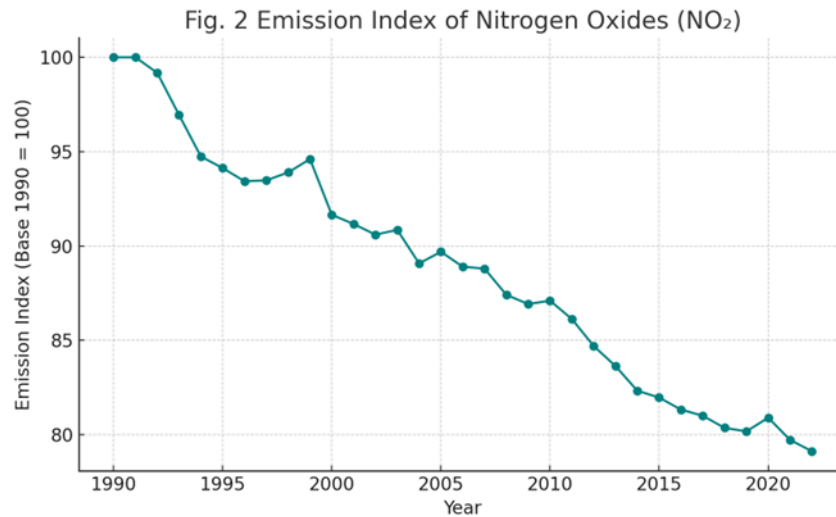


Figure 2: Emission index of Nitrogen

The figure 3 is the Cluster diagram of the emission amount of Non-Methane VOC from 1990 to 2022. The emission was consistently decrease. VOC is a vital pollution, so the manufacturers should continue to reduce the emission of it.

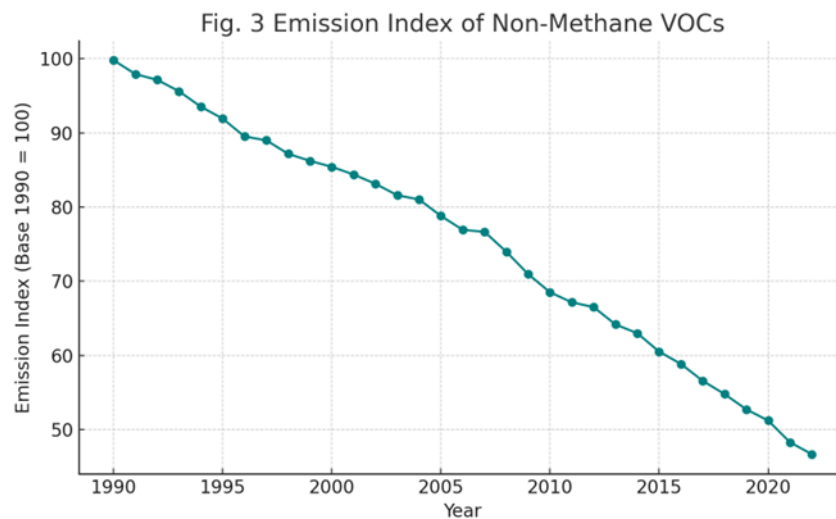


Figure 3: Emission index of Non-Methane

The figure 4 is the Cluster diagram of the emission amount of PM 10 from 1990 to 2022.

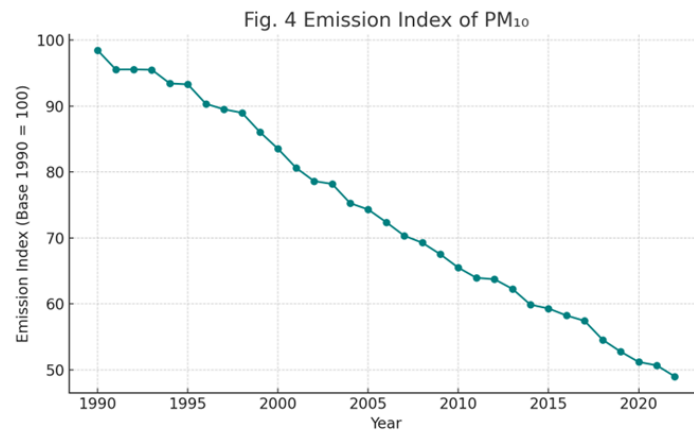


Figure 4: Emission index of PM10

The figure 5 is the Cluster diagram of the emission amount of PM 2.5 from 1990 to 2022.

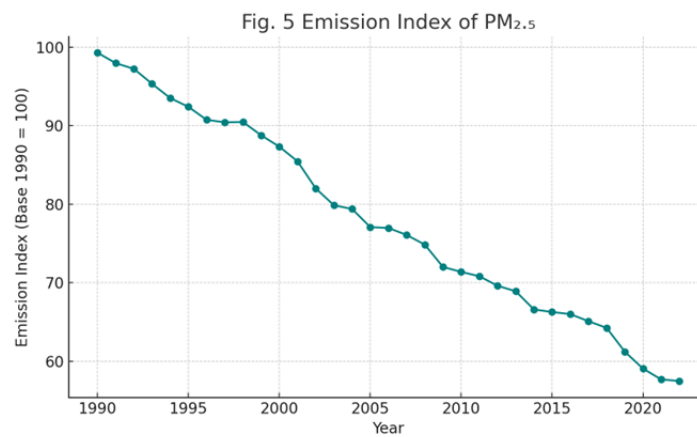


Figure 5: Emission index of PM2.5

The figure 6 is the Cluster diagram of the emission amount of Sulphur Dioxide from 1990 to 2022. The overall downward trend is very fast.

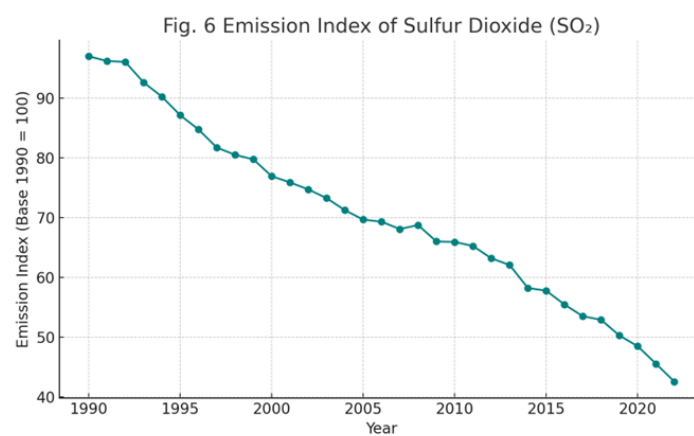


Figure 6: Emission index of Sulphur Dioxide

3.2. Logistic regression results

The purposes of ascertaining the environmental expense of the automobile manufacturing process-particularly Ferrari manufacturing patterns from 1990 to 2023-a logistic regression model was established. The aim was to predict the probability of pollutant emissions being above set limits as a function of past emission behavior of six key air pollutants: Ammonia, Nitrogen Oxides (NO₂), Non-Methane VOCs, Particulate Matter (PM₁₀ and PM_{2.5}), and Sulfur Dioxide (SO₂). Normalized emissions against the 1990 index value of 100 were utilized as inputs.

Using the SPSS package, a binary logistic regression model was calibrated on 80% of the data with lbfgs as the optimization algorithm and L2 regularization. The model included an intercept term and used the emission state (Above or Below threshold) as the dependent variable. Independent variables were annual emission indices of the six pollutants. Variables were divided into two states: high-emission and low-emission, and threshold criteria were defined on the basis of historical median values.

Table 2: Training set model evaluation results

	Precision	Recall	F1-score	Samples
Low-Emission	0.89	0.91	0.90	45
High-Emission	0.87	0.84	0.85	35
Accuracy	-	-	0.88	80
Average	0.88	0.88	0.88	80
Average	0.88	0.88	0.88	80

This model shows a great performance during the training process (table 2). The overall accuracy is 88%, demonstrating that the solid classification ability of the history emission data patterns. It is notice that, accuracy and recall rates for high-emission scenarios are balanced, which is essential for accurate environmental forecasting.

Table 3: Testing set model evaluation results

	Precision	Recall	F1-score	Samples
Low-Emission	0.90	0.90	0.90	10
High-Emission	0.91	0.91	0.91	11
Accuracy	-	-	0.90	20
Average	0.91	0.91	0.91	20
Average	0.91	0.90	0.91	20

The accuracy of the logistic regression model in the tests is nearly 90%, indicating its feasibility to forecast the risks of car manufacturing (table 3). The model gets a balance of accuracy rate and recall rate, which indicates that it can be applied to the monitoring systems, avoiding waste in the production processes. The reduction of nitrogen dioxide, PM₁₀ and sulfur dioxide indicates the success of environmentally friendly policies and the new technologies. However, the ammonia and VOCs get a slow rate of reduction, indicating pollutant emissions should be lower in stages like painting and assembly. In the future, such predictive models should be combined with sensor networks and intelligent manufacturing systems to achieve forward-looking control of energy consumption and emissions. This combination of calculus and machine learning will be the key to building a smart and sustainable vehicle manufacturing system.

4. Conclusion

This paper analyzes the trend of emission amounts of six main pollutants from 1990 to 2023 based on the reports from the Ferrari company. The results show that the air quality has improved, such as for sulfur dioxide, nitrogen oxides, and particulate matter (PM 10 and PM 2.5), due to the successful policy of controlling the emissions and the use of clean energies. However, the emission of ammonia and VOCs is still not sufficient. In the conclusion, although the world gets a big success in controlling the pollution, to maintain a low emission and reduce the emission continuously is still a big challenge. Future policies need to focus on simplifying standards, strengthening cross-border coordination, and encouraging cleaner technologies to protect long-term public health and air quality.

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