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Resolving the Ozone Dilemma: An Integration of Game Theory and Time Series Forecasting

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Abstract: The depletion of the ozone layer, a significant environmental concern, is primarily caused by human activities, particularly the emission of ozone-depleting chemicals like Chloro-Fluoro Carbons. Integrating machine learning (ML) and game theory methods presents a novel and promising approach to better anticipate and address this issue. Game theory offers a framework to model the interactions among various stakeholders, such as nations and industries, influencing the dynamics of ozone layer depletion, while large-scale dataset analysis through Time Series Forecasting and correlation enables more accurate predictions and informed decision-making. This study aims to enhance the accuracy of ozone layer depletion predictions by combining ARIMA time series forecasting, correlation with the Air Quality Index (AQI), and strategic decision-making through game theory. By incorporating the strategic interactions of various entities contributing to ozone layer depletion, the proposed interdisciplinary model seeks to provide realistic and comprehensive solutions for environmental sustainability and ozone protection. The methodology integrates ARIMA time series forecasting and correlation analysis to predict ozone depletion, with game theory modeling stakeholder interactions. This approach is designed to optimize policy-making and technological solutions to mitigate ozone depletion. The results show that ARIMA predicts future values with a Root Mean Squared Error of 5.04, while the game theory model generates tailored reports suggesting protocols for users. Additionally, correlation analysis reveals an 82% accuracy in relating AQI to ozone depletion using Gradient Boosting. This interdisciplinary approach demonstrates promising prediction accuracy and offers insights for improved decision-making in environmental sustainability. The findings underscore the importance of future research, international collaboration, and policymaking to protect the ozone layer and ensure the planet's environmental health.

Keywords: Ozone Layer Depletion, Machine Learning, Game Theory, Sustainability, Artificial Intelligence (AI)

1. Introduction

The ozone layer's thinning serves as a stark reminder of the effects of human activity on our planet amid an increasingly dire environmental situation. The stratosphere, a part of the Earth's atmosphere that is situated between 10 and 50 kilometers above the surface, is where ozone depletion mostly happens. The main culprit in this drama is chemical emissions, primarily from chlorofluorocarbons (CFCs), which eat away at the ozone layer that shields Earth from harm.

As the need to address this pressing issue grows, the use of cutting-edge technologies becomes essential. The primary objective of this study is to enhance the accuracy of ozone layer depletion predictions by integrating ARIMA time series forecasting, Air Quality Index correlation, and strategic decision-making through Game Theory, thereby offering a novel interdisciplinary model that incorporates the interactions between key stakeholders to inform more effective environmental policies and technological solutions. Situated in the Earth's stratosphere, the ozone layer is a thin layer of triatomic oxygen molecules that is essential for protecting life on Earth from damaging ultraviolet radiation. However, human activity has launched a relentless attack on this crucial layer, especially through the careless release of substances that deplete the ozone layer. The repercussions are severe, encompassing everything from a rise in skin cancer cases and cataracts in the eyes to extensive ecological disturbances.

Figure 1 showcases the ozone hole expansion from 1979-2011.The depletion of the ozone layer poses severe environmental and health risks. As the ozone layer thins, more of the Sun's ultraviolet (UV) radiation reaches the

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Earth's surface. This increased exposure to UV rays can lead to higher rates of skin cancer, cataracts, and other health issues. UVB radiation, in particular, has been linked to DNA damage in living organisms, which can result in various types of cancer and impair immune system functions.

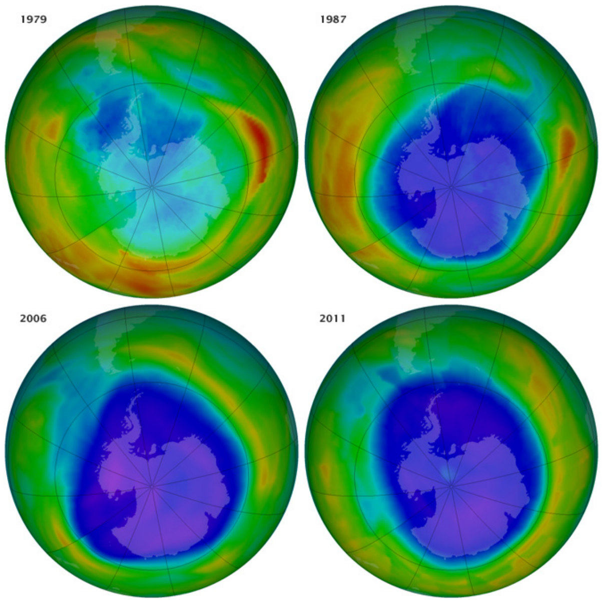

Figure 1. Ozone layer before and after the Montreal Protocol, cited from [1]

In addition to the human health impacts, ozone depletion also affects ecosystems. Marine life, especially plankton and fish larvae, is particularly vulnerable to increased UV radiation. Plankton forms the foundation of marine food chains, and its reduction could have widespread consequences for ocean biodiversity. On land, UV radiation can inhibit photosynthesis in plants, potentially reducing crop yields and harming forests.

An inventive, multidisciplinary approach is necessary to address the intricate web of interactions and choices that lead to ozone layer depletion. The application of machine learning and game theory to the problem of ozone layer depletion holds great potential for revolutionizing our understanding of and capacity for responding to environmental issues. This multidisciplinary approach gives policymakers and environmentalists powerful tools for developing focused and successful strategies, while also deepening our understanding of the complex dance of factors contributing to ozone layer depletion. The following sections contain related works, followed by the methodology proposed, the results of the experiments, and finally, we conclude with discussion and future works.

2. Related Works

Many investigations on the urgency, criticality, and scientific basis of the dilemma confronting mankind have been carried out by scholars in an effort to assess its seriousness. Numerous facets of the dilemma have been examined in these studies, from dangers to global health and climate change to biodiversity loss and environmental degradation. These studies' summaries provide us with a thorough understanding of the problems we face and emphasize how vital it is to find solutions. In [2],the authors examine ozone trends in relation to altitude, season, and latitude, comparing observed ozone data with different models. Total column ozone levels in the past and the future are estimated using two- and three-dimensional (2D and 3D) models. The authors in [3] classify the applications of game theory in various safety fields and suggest future research directions, aiding in the identification of trends and possible areas for growth. This study offers real-world game theory applications in several safety-related fields, including electrical, coal mine, construction, food, and traffic safety. In [4], the authors suggest a game-theoretic approach to address security and data trustworthiness (DT) issues in Wireless Sensor Networks (WSNs) for Internet of Things (IoT) applications, specifically using a repeated game. The main goals are detecting nodes experiencing hardware (HW) failures and thwarting selective forwarding (SF) attacks. Similarly, in [5], the authors propose a game-theoretic approach to tackle security and DT issues in WSNs. In [6], the authors formalize the links between game theory and machine learning, centering on the issue of drawing conclusions from prior observations, a major challenge in both domains. They incorporate algorithmic game theory ideas into the proposed methodology, modeling selfinterested agent behavior in the context of blockchain mining. The paper in [7] highlights the popular deep learning architecture known as GANs as a solution to difficult computer vision problems, illustrating how game theory is fundamental to the development of GANs, as GAN training is a two-player zero-sum game. In [8], the Borda scoring algorithm based on game theory was utilized to rank the GWQ conditioning factors based on sample points after creating the decision matrix for the ideal MCDM. The study in [9], based on an actual dataset of 982 construction projects, demonstrated that learning from prior bid sequences benefits contractors in the long run. Specifically, findings indicate that contractors can nearly double their chances of obtaining more projects by incorporating learning algorithms into the bidding process, increasing average profit by as much as 89.44 The authors in [10] utilize stochastic learning techniques to determine the equilibrium space of a molecule corresponding to stable or metastable conditions. According to [11], some of the causes of ozone depletion include chlorofluorocarbons (CFCs), uncontrolled rocket launches, global warming, and nitrogenous compounds such as NO, N2O, and NO2. In [12], the study examines the relationship between ozone layer alterations and the incidence of skin cancer, focusing on the notion of "environmental effective UVdose." Utilizing Norway's varied topography, the research evaluates how different ozone levels affect skin cancer, ensuring robust data through Norway's well-established cancer registry. The study in [13] advances our theoretical understanding of game theory in sustainable development education. Research in [14] aims to close a gap in prior research by establishing interdisciplinary research and teaching in the field of humanistic design, connecting design students with their living environment. The course is expected to assist students in developing multifaceted thinking and improve their capacity to incorporate meaningful game design. In [15], the quick development of Environmental Decision Support Systems (EDSS) is recognized, anticipating improvements in data sets, computing techniques, and spatial databases. Techniques for spatial visualization are acknowledged for enhancing decision-maker performance in terms of problem-solving speed, accuracy, and capability. The authors in [16] outline qualities of effective Decision Support Tools (DSTs) that can improve decision quality, emphasizing goal clarification, alternative identification, information gathering, and outcome tracking. Following extensive background research on the issue, the current study focuses on precise prediction and the creation of unified techniques for various use cases. This indicates that the goal of the study is to increase the precision of forecasts given in a specific context while ensuring uniformity and efficiency in decision-making processes.In [17] explore the application of machine learning models to predict the recovery of the ozone layer under various policy scenarios. Their research emphasizes the importance of integrating technological approaches with environmental policy frameworks to enhance predictive accuracy and guide decision-making processes. In [18] provide a comprehensive review of game theory applications in environmental management, highlighting the strategic interactions among stakeholders in managing environmental issues, including ozone depletion. Their work underscores the potential of game theory to inform collaborative approaches and optimize stakeholder engagement in environmental strategies. In a more technical contribution,in [19] utilize deep learning techniques for time series analysis to predict future trends in ozone depletion. Their study presents new methodologies that improve the predictive capabilities regarding ozone layer changes, demonstrating the effectiveness of advanced machine learning approaches in environmental research. Zhang and Wang in [20] propose a synergistic framework that combines machine learning and game theory to address the interlinkages between ozone depletion and air quality. This innovative approach provides insights into how these two domains can work together to formulate more effective environmental policies.In [21] focus on enhancing environmental strategies through the integration of artificial intelligence and game theory, presenting a case study on ozone layer protection. Their research emphasizes the significance of stakeholder interactions and the necessity for collaborative strategies in tackling environmental challenges.In [22] assess the effectiveness of various policy measures on ozone layer depletion using a game theoretic approach. Their study models stakeholder behavior to evaluate the impact of different policy interventions, providing valuable insights for policymakers aiming to mitigate ozone depletion effectively. The authors in [23] examine the application of machine learning techniques in forecasting ozone layer changes and associated health impacts. Their study emphasizes the need for robust predictive models that can incorporate various environmental variables and stakeholder actions to provide actionable insights for policymakers. In [24], the study investigates the role of game theory in developing cooperative strategies for ozone layer protection, illustrating how strategic interactions among nations can be modeled to facilitate international agreements and collective actions necessary for effective environmental governance. Nguyen and Tran in [25] utilize a hybrid approach combining machine learning and game theory to analyze the efficacy of policy measures aimed at mitigating ozone depletion. Their findings suggest that integrated frameworks can optimize decision-making processes and enhance the effectiveness of environmental policies. In [26] present a comprehensive study on the socio-economic implications of ozone layer depletion, employing game theoretical models to evaluate the trade-offs between economic growth and environmental sustainability, highlighting the importance of considering economic factors in environmental policy formulation. Finally, the authors in [27] explore the impact of climate change on ozone layer recovery through machine learning techniques, offering a predictive model that assesses the long-term effects of climate policies on ozone layer health, providing valuable insights for future environmental strategies.

The research on ozone depletion and environmental issues has predominantly focused on identifying trends, applying game theory to various safety fields, and improving predictive models. However, gaps remain in integrating these models with decision support systems (DSS) and in enhancing the accuracy of predictions by considering multiple stakeholders and dynamic policy interventions. Our paper addresses these gaps by combining game theory, machine learning, and DSS to provide a unified approach for more precise and collaborative environmental decision-making, particularly in the context of ozone layer protection. Additionally, we bridge the gap between technical advancements and policy frameworks, proposing integrated strategies for optimizing stakeholder engagement and forecasting future environmental trends

3. Proposed Methodology

The methodology for this study is structured to integrate time series forecasting with game theory to examine the relationship between ozone depletion and air quality in the Southern Hemisphere as seen in Figure 2.

The approach begins with the collection and merging of ozone hole data and air quality data, establishing a foundation for correlation analysis. Next, time series forecasting models, specifically ARIMA and SARIMA, are employed to predict future ozone hole trends. These predictions are then incorporated into a game theory framework, where government agencies and industries are modeled as strategic players with competing and cooperative strategies.

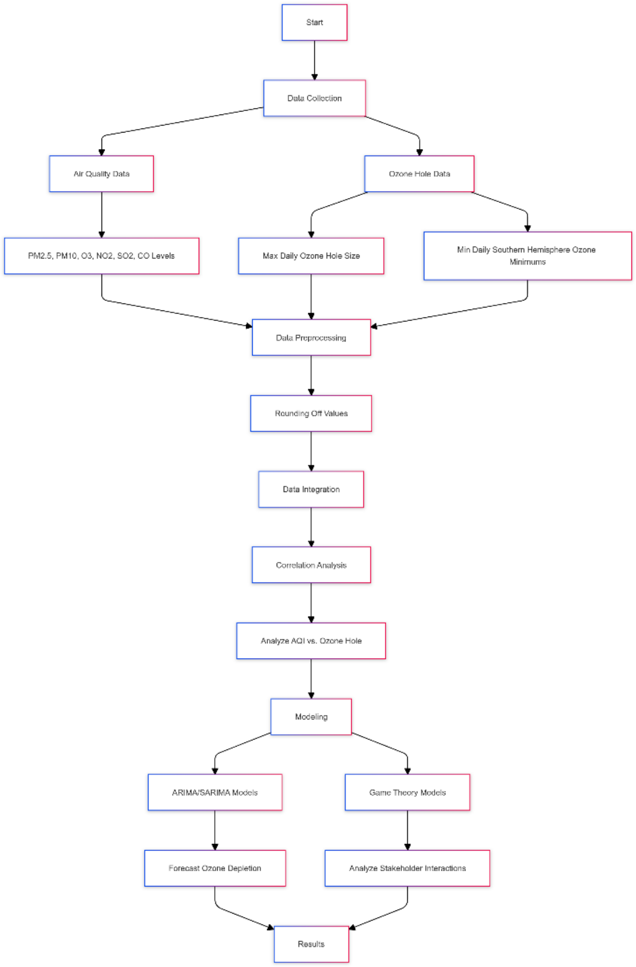

Figure 2. . Proposed Methodology

Through the use of Nash Equilibrium, Pareto efficiency, and Stackelberg leadership, the interactions between these stakeholders are explored, with the goal of understanding how different regulatory and technological strategies impact both the environment and the economy. The methodology ensures a dynamic feedback loop, where time series predictions inform strategic decision-making, ultimately providing insights into sustainable policy and industry practices.

A. Data Preparation

The data preparation phase of this study was crucial to integrate ozone depletion data with air quality data for the Southern Hemisphere. Ozone hole data, sourced from NASA's Ozone Hole Watch, included records of the maximum daily ozone hole size and minimum daily Southern Hemisphere ozone levels [28]. Air quality data, collected from the World Air Quality Historical Database, focused on Bringelly, a suburb in Sydney's southwest, Australia [29]. Both datasets were filtered to cover the same time frame, ranging from 2013 to 2024, ensuring temporal alignment. Pre-processing involved cleaning and merging these datasets to create a unified structure. Missing values were handled to maintain consistency and accuracy, and time series data was formatted for forecasting analysis. The combined dataset served as the foundation for examining correlations and implementing game theory strategies to explore the interplay between ozone depletion and air quality.

B. Exploratory Data Analysis

The authors performed exploratory data analysis on the data to understand the underlying behaviors in the patterns involved. The consumption of ozone-depleting substances has reduced significantly over the past decade, with the peak being in the 1980s, as seen in Figure 3 and Figure 4.

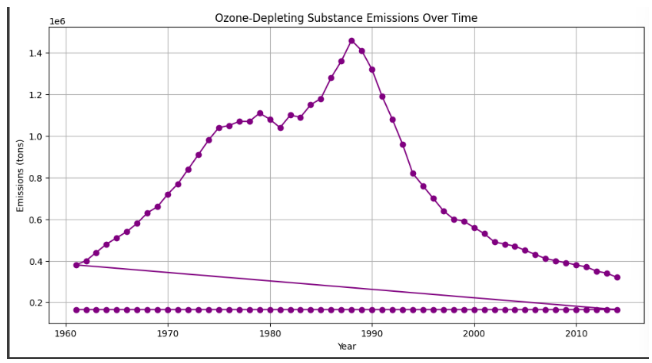

Figure 3. Ozone Depleting Substance Emission Over Time: A Downward Slope

The insights acquired from trend analysis for ozonedepleting substance emissions show that the mean emission is 465,462.96 tons. The year with the highest average emissions was 1988, with 812,500.00 tons of substances emitted, while the lowest average was in 2014, with 242,500.00 tons emitted. Over the years, the entity with the highest consumption of Methyl Chloroform (TCA) and Methyl Bromide (MB) was the United States, while Asia had the highest consumption of Hydrochlorofluorocarbons (HCFCs) and Halons. For Carbon Tetrachloride (CTC) and Chlorofluorocarbons (CFCs), the highest consumers were China and Europe, respectively. The overall lowest consumption of substances TCA, MB, HCFCs, CTC, Halons, and CFCs was noted in Afghanistan, Ukraine, Niue, the United States, Africa, and Vatican City, respectively. The correlation metrics highly suggest that over the years, the consumption of Methyl Chloroform and Chlorofluorocarbons (CFCs) are highly correlated.

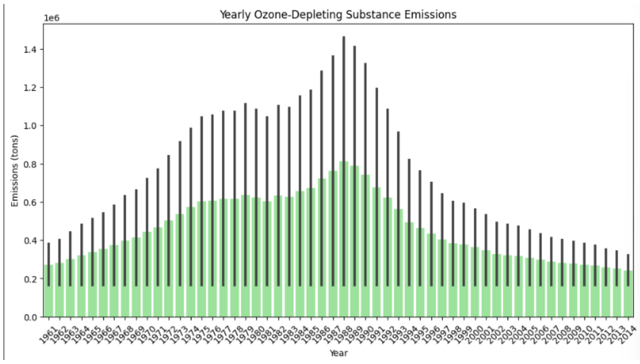

Figure 4. Emission Peaks in the 1980s

Parties involved in environmental agreements from 1971-2015, when consolidated, provide insights into the global landscape of agreements, participation over time, and their relationships. The agreement with the highest number of parties was the World Heritage Convention, with 5,321 parties, while the one with the lowest was the Rotterdam Convention, with 1,691 parties. A steep increase in participation was observed in the World Heritage Convention, which had 30,374 parties, while the steepest decrease was with the Kyoto Protocol, which saw a decrease of 2,832 parties.

Figure 5 visually represents projected changes over time since 1960, quantifying ozone depletion and highlighting critical periods where significant changes occurred.

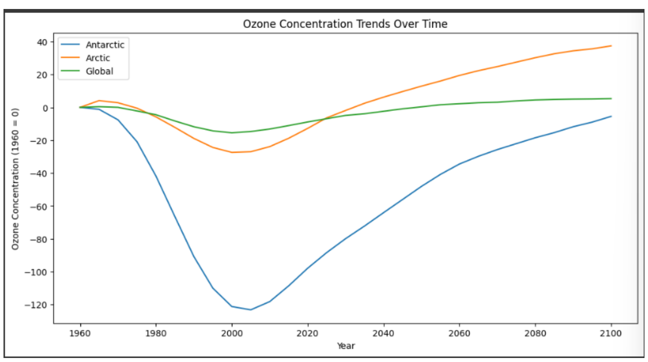

Figure 5. Stratospheric Ozone Concentration Projections

The mean, maximum, and minimum ozone concentration occurred at -16.97 units, 37.40 units (in 2100), and -123.20 units (in 2005), respectively, plotted region-wise (Antarctic, Arctic, and Global as seen in Figure 6.) for a detailed understanding.Global insights indicate that the year with maximum change was 2020.

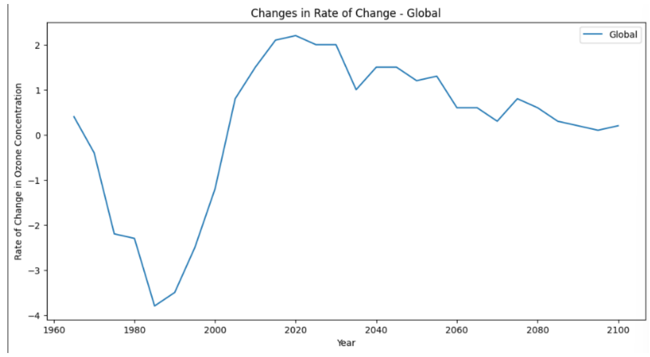

Figure 6. Change in Rate of Ozone Concentration

Figure 7 is valuable for understanding the distribution of CFC emissions globally. When integrated into game-theory models, it enhances the analysis and strategic interactions among stakeholders.

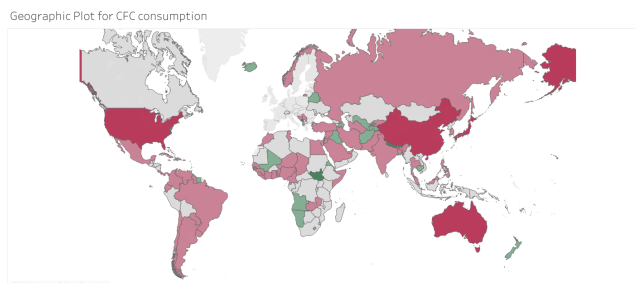

Figure 7. Geographic Plot for CFC Consumption

Figure 8 displays trends in air quality pollutants from 2017 to 2023, highlighting key pollutants such as PM2.5,PM10, O3, NO2, SO2, and CO. This figure is important for understanding the temporal changes in pollution levels during this period, offering insights into the effectiveness of environmental regulations and industrial practices.

Finally, Figure 9 depicts the ozone hole area and minimum ozone levels over time from 1979 to 2023, illustrating the temporal changes in the size of the ozone hole and the corresponding lowest ozone concentrations, highlighting key periods of ozone depletion and potential signs of recovery following international environmental policies like the Montreal Protocol.

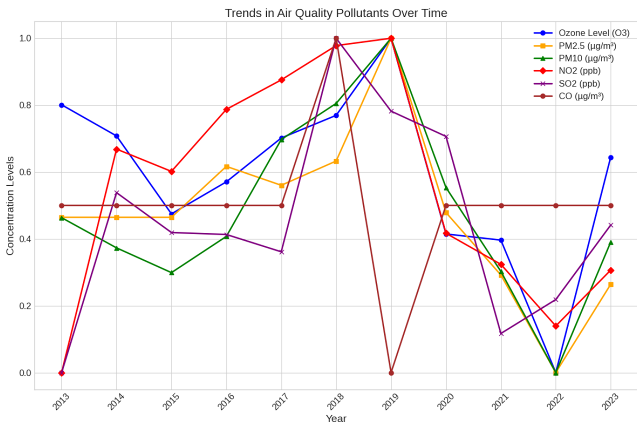

Figure 8. Trends in Air Quality Pollutants over Time (2017-2023)

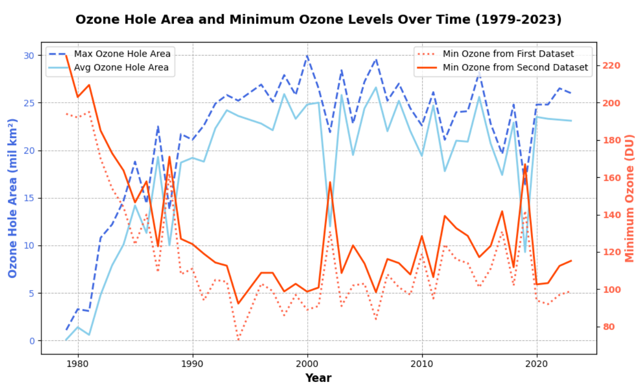

Figure 9. Ozone Hole Area and Minimum Ozone over Time (1979-2023)

C. Time Series Forecasting for Ozone Layer Depletion and Air Quality Index Forecasting

To predict future trends in ozone depletion, we employed two types of time series models: ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal ARIMA). These models are particularly suited for handling time-dependent data, accounting for trends, seasonality, and autocorrelations inherent in environmental datasets such as ozone hole data. Below is a detailed explanation of how these models were selected, calibrated, and validated, with mathematical details.

1) **ARIMA Model Selection and Calibration**
ARIMA is a popular statistical method for forecasting time series data, defined by three parameters: p, d, and q, which represent the autoregressive order, the degree of differencing, and the moving average order, respectively. The general form of the ARIMA model can be written as:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{1}$$

where Y_t is the value at time t, c is a constant, ϕ_i and θ_j are the AR and MA parameters, ϵ_t is the error term, and p, d, q are the model's order parameters.

- p, d, q values were determined through ACF (AutoCorrelation Function) and PACF (Partial AutoCorrelation Function) plots to identify lag correlations and differencing requirements.
- The model was then fitted to the ozone hole data to make forecasts. Through cross-validation, the best-fit ARIMA model was selected for ozone hole trend predictions.

2) **SARIMA Model Selection and Calibration**
Given the strong seasonal patterns in ozone depletion, a SARIMA (Seasonal ARIMA) model was employed to better capture these periodic fluctuations. SARIMA extends the basic ARIMA model by incorporating seasonal differencing and seasonal autoregressive/moving average terms. The SARIMA model is expressed as:

$$\begin{aligned}(1 - \sum_{i=1}^{p} \phi_i L^i)(1 - \sum_{j=1}^{P} \Phi_j L^{js})(1 - L)^d y_t = \\ (1 + \sum_{k=1}^{q} \theta_k L^k)(1 + \sum_{m=1}^{Q} \Theta_m L^{ms})\epsilon_t\end{aligned} \tag{2}$$

where L is the lag operator, $\phi_1, \phi_2, \ldots, \phi_p$ and $\Phi_1, \Phi_2, \ldots, \Phi_P$ are the autoregressive parameters for non-seasonal and seasonal components, $\theta_1, \theta_2, \ldots, \theta_q$ and $\Theta_1, \Theta_2, \ldots, \Theta_Q$ are the moving average parameters for non-seasonal and seasonal components, d is the degree of differencing, s is the seasonal period, y_t is the observed value at time t, and ϵ_t is the error term at time t.

- The seasonal parameters P, d, Q, s were identified using seasonal autocorrelation plots to detect repetitive patterns in the ozone depletion data. The seasonal terms helped the model adjust for recurring annual fluctuations in the ozone hole size, making SARIMA highly suitable for this application
- The model was then calibrated by fitting it to historical data and performing forecasts based on seasonal and trend patterns

D. Modeling Approach and Implementation

In the context of this research, the ARIMA and SARIMA models were applied to forecast the future behavior of the ozone hole area using the following steps:

1) **Preprocessing:** The raw ozone hole dataset was transformed to make it stationary through differencing (removing trends), and ACF/PACF plots were used to determine the values of p, d, and q.
2) **Model Training:** The ARIMA and SARIMA models were trained using historical ozone hole size data, with a focus on capturing both short-term variations

(using ARIMA) and long-term seasonal patterns (using SARIMA).

3) **Validation:** The models were validated by testing on holdout data, comparing the predicted ozone hole sizes with the actual observed values.
4) **Forecasting:** Once the models were fine-tuned, they were used to forecast future trends in ozone depletion over a defined time period.

E. Game Theory Integration

Game theory provides a structured framework for analyzing strategic interactions between two key players involved in the ozone depletion dilemma: government agencies and industries. The choices made by each player not only affect their respective outcomes but also have broader implications for environmental health and public welfare. For the purposes of this study, we focus on this specific scenario involving government agencies and industries; however, it's important to acknowledge that this framework can be adapted to include other stakeholders, such as environmental NGOs or the public, in future analyses.

1) **Player 1: Government Agencies**
   a) **Minimal Regulation:** Government agencies may choose to implement basic regulations with limited enforcement. This strategy aims to minimize administrative costs while allowing some level of ozone depletion to continue, prioritizing short-term economic gains over long-term environmental health.
   b) **Strict Regulation:** Alternatively, government agencies can opt for strict regulations on pollutants that deplete the ozone layer. This strategy seeks to significantly reduce emissions, promote environmental recovery, and ultimately improve air quality. The long-term benefits of such measures may outweigh the immediate economic impacts, fostering a healthier ecosystem.
2) **Player 2: Industries**
   a) **Business as Usual:** Industries may decide to continue current practices without making significant changes. This strategy focuses on maximizing short-term profits but often results in increased emissions and exacerbates ozone depletion.
   b) **Adoption of Green Technologies:** In contrast, industries may invest in and implement cleaner technologies to reduce emissions of ozone-depleting substances. This strategy aligns with long-term sustainability goals and can lead to benefits from regulatory support and consumer preferences for eco-friendly products.

1) Nash Equilibrium

In game theory, a Nash equilibrium occurs when both players select strategies such that neither would benefit from unilaterally changing their decision. The following scenarios illustrate potential Nash equilibria:

1) **Scenario 1: (Minimal Regulation, Business as Usual)** Both government agencies and industries maintain the status quo, resulting in ongoing ozone depletion and deteriorating air quality. While this is a stable outcome given their choices, it is ultimately detrimental to environmental health.
2) **Scenario 2: (Strict Regulation, Adoption of Green Technologies)** In this equilibrium, both players adopt environmentally conscious strategies. Government agencies enforce strict regulations, prompting industries to invest in green technologies. This leads to ozone layer recovery and improved air quality, representing a mutually beneficial outcome where both players align toward environmental sustainability.

The concept of Nash Equilibrium extends beyond just these two players and can be applied to international negotiations, as nations must decide how much effort to invest in reducing emissions. In this broader context, the Nash Equilibrium describes a situation in which no nation can unilaterally change its approach to emissions reduction without considering the strategies of others. Understanding this concept can guide policymakers in crafting strategies that are robust against the actions of other stakeholders.

Algorithm 1 Nash Equilibrium

```
Input: Set of players P = {p_1, p_2, ..., p_n}; Set of strategies for each player S = {S_1, S_2, ..., S_n}
Output: Nash equilibrium strategies
Initialize equilibriumFound ← false
while not equilibriumFound do
    for each player p_i ∈ P do
        Calculate the payoff for each strategy S_i ∈ S
        for each player p_i ∈ P do
            if p_i has a strategy S_i that gives a higher payoff than their current strategy then
                Update p_i's strategy to S_i
            end if
        end for
    end for
    if all players have strategies giving them maximum payoff then
        set equilibriumFound ← true
    end if
end while
return strategies for each player at equilibrium
```

2) Pareto Efficiency

This study also examines Pareto-efficient outcomes, where an improvement in one player's strategy does not harm the other player's outcome. For instance, if government agencies implement stricter regulations that lead to better environmental outcomes without adversely affecting industry profits (e.g., through subsidies or incentives for green technologies), both players can benefit. Achieving Pareto efficiency signifies a win-win situation, allowing both players to enhance their respective outcomes.

Algorithm 2 Pareto Efficiency

```
Input: Decision variables: x_i for each player i; Utility functions: U_i(x_1, x_2, ..., x_n) for each player i; Feasible outcome space: X
Output: Pareto optimal solutions x*
Define Decision Variables: Let x_i represent the decision variable for each player i in a strategic interaction.
Formulate Utility Functions: Define the utility function U_i(x_1, x_2, ..., x_n) for each player i.
Identify Feasible Outcome Space: Define the feasible outcome space X as the set of all possible combinations of decision variables that satisfy constraints.
Find Pareto Optimal Solutions:
for each solution x* in the feasible outcome space X do
    Evaluate the utility U_i(x*) for each player i.
    if there exists another feasible solution x' such that then
        U_i(x') ≥ U_i(x*) for all players i, and U_j(x') > U_j(x*) for at least one player j
    end if
    if no such solution x' exists then
        x* is a Pareto optimal solution.
    end if
end for
return the set of Pareto optimal solutions x
```

3) Stackelberg Leadership

The Stackelberg model is utilized to simulate situations where one player—government agencies—assumes a leadership role by imposing regulations. The other player—industries—reacts by adjusting their strategies in response. This dynamic underscores the significance of policymakers in guiding industries toward sustainable practices. For example, when government agencies enforce strict regulations, industries may be compelled to adopt greener technologies, recognizing the long-term benefits of compliance and sustainability.

Algorithm 3 Stackelberg Leadership

```
Input: Players: Leader and followers; Strategies: Strategy sets for each player; Payoff Functions: Payoff functions representing each player's utility given their chosen strategies; Leader's Commitment: Strategy chosen by the leader before followers make their decisions
Output: Optimal Strategy for the Leader
Define Leader and Followers: Designate one player as the leader and the rest as followers.
Leader Commits to Strategy: Specify the leader's commitment by choosing a strategy s_L.
for each follower i do
    Observe the leader's chosen strategy s_L.
    Choose their own strategy s_i to maximize their payoff given s_L.
end for
Leader Anticipates Followers' Responses: Anticipate how followers will respond to the leader's chosen strategy s_L.
Determine Optimal Strategy for the Leader: Evaluate the outcomes to determine the effectiveness of the leader's strategy in influencing follower behavior.
return the leader's chosen strategy s_L that maximizes the leader's payoff given the anticipated responses of the followers.
```

F. Game Theory Protocol Integration

In addition to modeling the strategic interactions, we developed a program to generate custom reports based on stakeholder data requirements. Whenever a user requests a report, the program dynamically creates it by calling predefined functions. Furthermore, the program includes details about suggested protocols related to ozone protection based on entered keywords. These protocols include:

- **The Vienna Convention for the Protection of the Ozone Layer (1985)**: A framework agreement for international cooperation to protect the ozone layer.
- **Montreal Protocol (1987)**: A global agreement aimed at phasing out ozone-depleting substances (ODS) like chlorofluorocarbons (CFCs) and halons.
- **The Copenhagen Amendments (1992)**: Strengthening commitments by enhancing control measures and accelerating phase-out schedules in response to evolving scientific understanding.
- **The Beijing Amendment (1999)**: Focused on phasing out hydrochlorofluorocarbons (HCFCs), which are both ODS and potent greenhouse gases.
- **The Kigali Amendment (2016)**: Aims to reduce the consumption of hydrofluorocarbons (HFCs), potent greenhouse gases that are alternatives to ODS.

Table I contains the protocols mentioned above by the year.

Through game theory modeling and protocol integration, we gain valuable insights into the interactions between government agencies and industries in addressing ozone depletion. The analysis of strategies, Nash equilibria, Pareto efficiency, and leadership dynamics provides a comprehensive understanding of how collaborative approaches can lead to environmentally sustainable outcomes. This study highlights the significance of understanding Nash Equilibrium not only in strategic interactions between government and industry but also in broader international negotiations aimed at reducing emissions. While this study focuses on the

TABLE I. Ozone Protection Protocols

Year	Protocol
1985	The Vienna Convention for the Protection of the Ozone Layer
1987	Montreal Protocol
1992	The Copenhagen Amendments
1999	The Beijing Amendment
2016	The Kigali Amendment

interplay between government and industry, the game theory framework can be adapted to include other stakeholders, enhancing the robustness of future analyses. Ultimately, these insights can inform policymakers and stakeholders in developing effective strategies to combat ozone layer depletion while considering the economic implications for industries and the broader community.

4. Results

Figure 10 is the forecasting output for ARIMA model.Time series data that is non-stationary can be used with ARIMA models. Three elements distinguish them: moving average (MA), differencing (I), and autoregression (AR). ARIMA models are adaptable and have a broad range of data patterns that they can manage. They do, however, require the data to remain steady, which might be why our model predicts with better accuracy

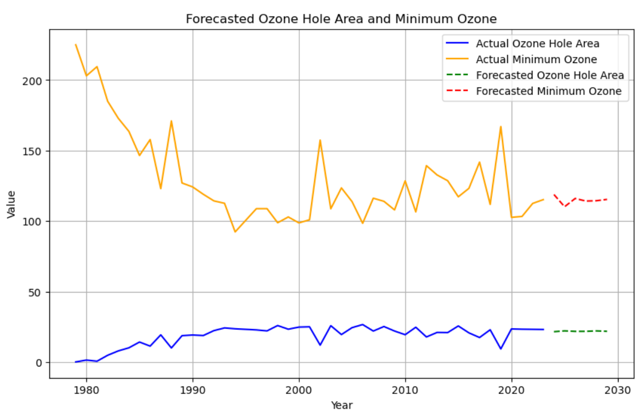

Figure 10. Forecasting Output ARIMA

Figure 11 contains output using Exponential smoothing.A more straightforward technique is exponential smoothing, which gives historical observations exponentially decreasing weights. It works well with data that lacks seasonality or a discernible pattern. Exponential smoothingmodels are computationally efficient and simple to comprehend. They might not function effectively, though, when dealing with data that has intricate patterns. SARIMA is an extension of ARIMA that manages data seasonal trends. It has extra moving average, differencing, and seasonal autoregression parameters. When seasonal tendencies are present in the data, SARIMA is helpful since it can accurately capture these patterns. SARIMA models can be

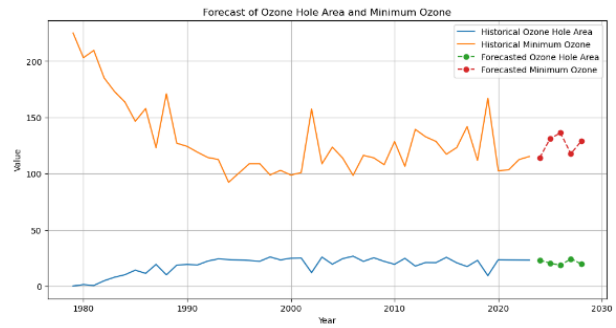

Figure 11. Forecasting output Exponential Smoothing

difficult to set up, and additional data could be needed for precise predictions. Figure 12 contains forecasting output using SARIMA. Table II summarizes the results of various models tested.

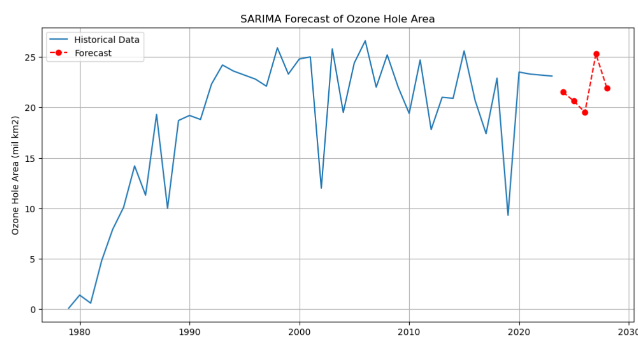

Figure 12. Forecasted Ozone Hole Area using SARIMA

TABLE II. Model Predictions

Model	Metric	Value
ARIMA	Mean Absolute Error	4.056
	Mean Squared Error	25.454
	Root Mean Squared Error	5.045
SARIMA	Mean Absolute Error	8.16
	Mean Squared Error	83.93
	Root Mean Squared Error	9.16

Figure 13 presents the Average Pollution Levels for key pollutants—PM2.5, PM10, O, NO, SO, and CO—by year.

This figure is essential as it visualizes trends in air quality over time, enabling us to observe patterns of pollution and potential correlations with environmental changes, such as ozone layer depletion. By comparing these pollutants annually, we can assess the impact of regulatory policies and industrial practices on air quality and understand how pollution levels have evolved alongside ozone depletion trends.

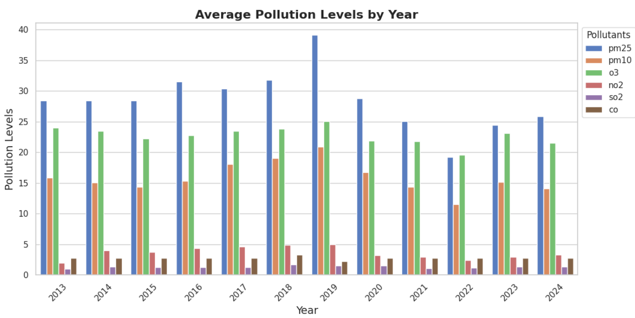

Figure 13. Average Pollution Levels by Year for Pollutants PM2.5, PM10, O, NO, SO, CO

The study in [30] used Air Quality Indices as a tracer for atmospheric stability. Major pollutants are particulate matter (PM2.5 and PM10), sulfur dioxide (SO), nitrogen dioxide (NO), ozone (O), carbon monoxide (CO), and ammonia (NH) [31]. Of the gases listed, sulfur dioxide(SO), nitrogen dioxide (NO), and carbon monoxide (CO) are not greenhouse gases, while ozone (O) and ammonia (NH) are considered greenhouse gases and directly affect the ozone layer.

Figure 14 shows the correlation between AQI and Ozone Hole Area, highlighting key relationships between ozone depletion and air pollutants:

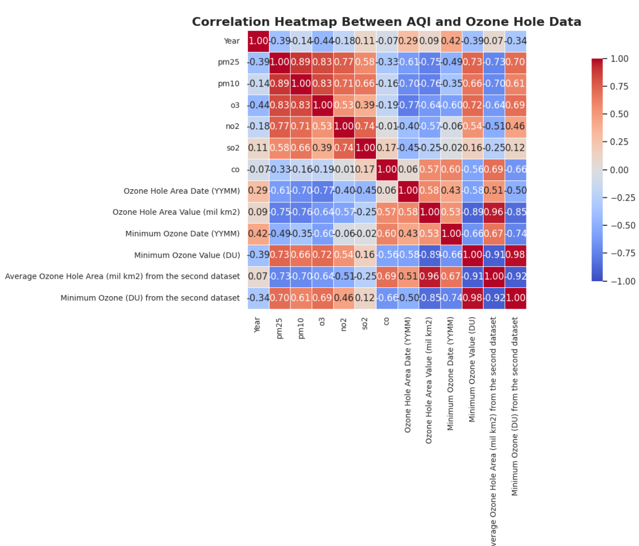

Figure 14. Correlation between AQI and Ozone Hole

- Strong negative correlations with PM2.5 (-0.75), PM10 (-0.76), O (-0.64), and NO (-0.57) indicate that pollutant levels decrease as the ozone hole expands.
- Weak correlation with SO (-0.25) suggests less interaction.
- Positive correlation with CO (0.57) shows rising carbon monoxide levels as the ozone hole increases.
- The Ozone Hole Area correlates strongly with its own measurements and dates, confirming consistency across datasets.

These insights highlight the connection between ozone depletion and air quality, informing potential policies for environmental protection.

A. *Game Theory Models Results*

Implications of Nash Equilibrium Outcomes. These equilibria are stable outcomes where neither player can unilaterally improve their payoff. Mixed strategies reflect a more complex scenario where players consider various risks and rewards.

- **Nash Equilibrium Outcomes:**
  - (1, 0), (1, 0) - **Pure Strategy Equilibria**: Both players exclusively choose their first (Maximal Regulation) strategy.
  - (0, 1), (0, 1) - **Mixed Strategy Equilibrium**: Players use probabilistic strategies, balancing risk and payoff.

Implications of Pareto Efficiency Outcomes. Payoff structure may need adjustments for Pareto improvements.

- **Pareto Efficiency Outcomes:**
  - **No Pareto Efficient Points**: No combination of strategies benefits one player without harming the other. This indicates that any potential gain for one player comes at a loss to the other.

Implications of Stackelberg Leadership Outcomes. Minimal regulation supports short-term industrial gains but may cause environmental damage. Strict regulation achieves environmental goals but could result in economic inefficiency for industries, making compliance challenging.

- **Stackelberg Leadership Outcomes:**
  - **Minimal Regulation: Follower Payoff = 2**: Industries benefit from minimal regulation but struggle under strict regulation due to higher costs or restrictive practices.
  - **Strict Regulation: Follower Payoff = 0**: Government strategies directly impact industrial payoffs.

5. Conclusions and Future Work

This study successfully demonstrated that combining time series forecasting with game theory is a powerful framework for examining the complexities of ozone depletion and air quality management. The predictive models (ARIMA and SARIMA) provided valuable forecasts for future ozone layer trends, highlighting periods of potential recovery and risk. Game theory analysis showcased how strategic decisions made by government agencies and industries could either mitigate or exacerbate ozone depletion. The ARIMA model forecasted future values, achieving a Root Mean Squared Error of 5.04. The Game Theory approach produces customized reports based on user requirements, recommending specific protocols. Additionally, the authors found an 82% accuracy in correlating the Air Quality Index with Ozone Layer Depletion using Gradient Boosting. Key findings suggest that stricter environmental regulations coupled with the adoption of green technologies by industries are critical to achieving long-term ozone recovery. In particular, the Nash Equilibrium outcome (strict regulation, green technology adoption) offers a path toward sustainable environmental management. Additionally, Paretoefficient outcomes provide policymakers with insights into how to design policies that ensure both environmental protection and industrial viability. The Stackelberg leadership model further emphasizes the importance of government leadership in driving industrial change. This research adds to the growing body of literature on the relationship between human activities and the environment, providing valuable insights into the interplay between regulatory frameworks, industrial actions, and environmental health. The integration of game theory offers a unique way to examine how different stakeholders can collaborate to address environmental challenges. We offer a comprehensive framework for analyzing ozone depletion and air quality, with several avenues for future research. First, incorporating additional stakeholders like NGOs and the public would provide a more holistic view of environmental policy-making. Second, utilizing dynamic game theory models could simulate realtime policy shifts and industry reactions. While ARIMA and SARIMA models are useful, integrating advanced machine learning techniques like Long Short-Term Memory (LSTM) or Prophet could improve long-term forecasting. Expanding the analysis to include global air quality and ozone depletion patterns, particularly in the Arctic and industrial regions, would enhance generalizability. A detailed economic impact analysis of green technology adoption and stricter regulations would further enrich the findings, along with considering social factors such as public health benefits. Employing multi-objective optimization algorithms within the game theory framework could help balance environmental, economic, and social goals. Lastly, assessing the long-term effectiveness of international protocols like the Montreal Protocol would provide critical insights for future environmental agreements.

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