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

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ABSTRACT

The main cause of the ozone layer's depletion, which is a serious environmental problem, is human activity such as the emission of chemicals that deplete the ozone layer, like Chloro-Fluro Carbons. The combination of machine learning (ML) and game theory methods appears to be a novel and promising way to better anticipate and address ozone layer depletion. The interactions between different stakeholders, such as nations or industries, that affect the dynamics of the ozone layer can be modeled using a framework provided by game theory. In the meantime, large-scale dataset analysis made possible by Time Series Forecasting along with correlation allows for more precise forecasts and well-informed decision-making. This study's main goal is to improve the accuracy of ozone layer depletion predictions by utilizing ARIMA Time Series forecasting, correlation with the Air Quality Index along with the science of strategy for better decision-making via Game Theory. The proposed methodology has proposed a way to create a more realistic and comprehensive model by taking into account the strategic interactions among various entities that contribute to the depletion of the ozone layer. By using an interdisciplinary approach, we hope to aid in the creation of practical plans for environmental sustainability and ozone layer protection. ARIMA predicted the values for the upcoming years, with a Root Mean Squared Value of 5.04. The Game Theory approach generates a report tailored to the needs of the user suggesting the protocols to be followed. Finally, the authors also correlated the Air Quality Index with the Ozone Layer Depletion with an accuracy of 82% with Gradient Boosting.

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. The use of cutting-edge technologies becomes essential as the need to address this pressing issue grows. In this endeavor, the combination of game theory and machine learning (ML) presents a novel approach with the potential for increased prediction accuracy and a more tactical approach to environmental preservation. 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. But human activity has launched a relentless attack on this crucial layer, especially 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. 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.

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 this research, from dangers to global health and climate change to biodiversity loss and environmental degradation. These studies' summaries provide us a thorough understanding of the problems we face and emphasize how vital it is to find solutions. In [1] the authors examine ozone trends in relation to altitude, season, and latitude. The study compares 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 [2] aid in the identification of trends and possible areas for growth by classifying the applications of game theory in various safety fields and suggesting future research directions. The study offers real-world game theory applications in a number of safety-related fields, including electrical, coal mine, construction, food, and traffic safety. In [3] the authors in order to address security and data trustworthiness (DT) issues in Wireless Sensor Networks (WSNs) for Internet of Things (IoT) applications, suggest a game-theoretic approach, specifically using a repeated game. The main goals are detecting nodes experiencing hardware (HW) failures and thwarting selective forwarding (SF) attacks. Systems for detecting intrusions (IDS). The authors in [4] in order to address security and data trustworthiness (DT) issues in Wireless Sensor Networks (WSNs) for Internet of Things (IoT) applications, suggest a game-theoretic approach, specifically using a repeated game. In [5] in an effort to formalize the links between game theory and machine learning, the paper examines their shared ground. It centers on the issue of drawing conclusions from prior observations, which is a major issue in both domains. The authors incorporate algorithmic game theory ideas into the suggested methodology. In particular, self-interested agent behavior is modeled using game theory in the context of blockchain mining. In [6] the popular deep learning architecture known as GANs is highlighted in the paper as a solution to difficult computer vision problems. The idea that GAN training is a two-player zero-sum game illustrates how game theory is fundamental to the development of GANs. In [7] the Borda scoring algorithm based on GT was used to rank the GWQ conditioning factors based on sample points after the decision matrix for the ideal MCDM was created. In this algorithm, the criteria, alternatives, and GWQ conditioning factors were sample points. In [8] the study based on an actual dataset of 982 construction projects, the study's findings demonstrated that learning from prior bid sequences benefits contractors in the long run by helping them win more projects or lessen the winner's curse. More specifically, the findings demonstrate that contractors can nearly double their chances of ultimately obtaining more projects by incorporating learning algorithms into the bidding process. Additionally, compared to the case where no learning algorithm was used in the bidding decision, the average profit for the collected dataset increased by as much as 89.44% as a result of the application of learning algorithms. The authors in [9] their main concept is to use stochastic learning techniques to determine the equilibrium space of a molecule that corresponds to stable or metastable conditions. From [10] some of the Ozone Depletion Causes are: Chlorofluorocarbons (CFCs): Although once thought to be the primary cause of ozone depletion, CFCs are now disputed as the main contributors. Uncontrolled Rocket Launches: It is predicted that uncontrolled rocket launches will contribute more to ozone loss by 2050 than CFCs. Global Warming: The heat held in the troposphere keeps sunlight needed for ozone layer recovery from reaching the stratosphere, which indirectly contributes to ozone layer depletion. Nitrogenous Compounds: The depletion of the ozone layer is also greatly aided by the emission of nitrogenous compounds such as NO, N_2O, and NO_2. In [11] the study examines the relationship between ozone layer alterations and the incidence of skin cancer, with a particular emphasis on the notion of "environmental effective UV-dose." It makes use of Norway's varied topography, which stretches from north to south, to evaluate how different ozone levels affect skin cancer. Robust data is ensured by utilizing Norway's well-established cancer registry and a skin-type homogeneous population. Four latitude-ranging regions are chosen for the geographical analysis in order to thoroughly investigate skin cancer incidence in relation to varying UV exposures. Under the assumption of normal ozone conditions, the study computes annual effective UV-doses for these regions using the CIE action spectrum up to 400 nm. The study in [12] advances our theoretical understanding of game theory in sustainable development education. In [13] closes a gap in prior research: By establishing interdisciplinary research and teaching in the field of humanistic design and establishing a connection between design students and their living environment, the research aims to close a gap in prior research. Multifaceted Thinking Development: It is said that this course will assist students in developing multifaceted thinking and improve their capacity to incorporate meaningful game design. In [14] Quick Development of EDSS: Recognizes that EDSS has advanced quickly, anticipating improvements in the form of consistent data sets, computing techniques, and spatial databases. Techniques for Spatial Visualization: Acknowledges the advantages of these methods, which include enhanced decision-maker performance in terms of problem-solving speed, accuracy, and ability. The authors in [15] Improving Decision Quality: Outlines qualities of effective DSTs that can improve decision quality, such as goal clarification, identification of alternatives, information gathering, articulation of values, assessment of alternatives, and outcome tracking. CPRA as an Exemplar: With support from stakeholders, this statement presents CPRA's process and tool as an example of participatory integrated risk assessment and planning. Following extensive background research on the issue, precise prediction and the creation of unified techniques for a range of use cases have been determined to be the primary areas of focus for the current study. This indicates that the goal of the study is to increase the precision of forecasts given in a certain subject or situation. It also aims to create methods that are applicable to many situations or uses in that sector, guaranteeing uniformity and efficiency in the processes of making decisions or addressing problems. This strategy is essential for guaranteeing that the study's suggested remedies are precise, flexible, and scalable to handle a variety of problems or demands inside the research area.

3. METHODS

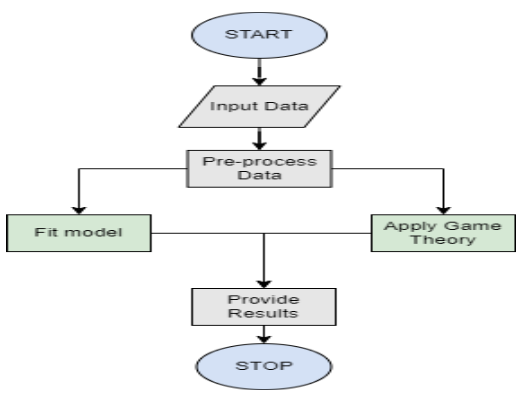

Figure 1. Proposed Methodology

The methodology incorporates a variety of analytical and computational tools to provide a comprehensive approach to understanding and managing ozone layer depletion, emphasizing the value of interdisciplinary collaboration and strategic decision-making.

3.1 Exploratory Data Analysis

The proposed methodology performed exploratory data analysis on the data to understand the underlying behaviors in the patterns involved. Consumption of ozone-depleting substances has reduced significantly over the past decade, the peak being in the 1980s as seen in Figure.2 and Figure 3.

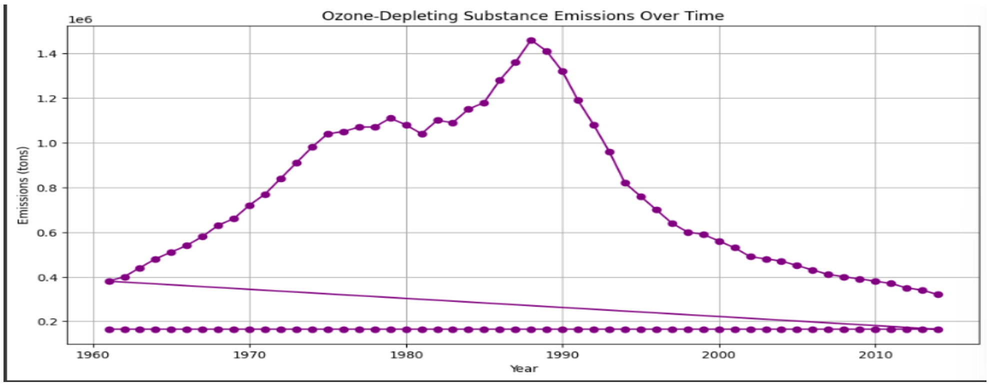

Figure. 2 Ozone Depleting Substance Emission Over Time:
A Downward Slope

The insights acquired from trend analysis for Ozone depleting Substance Emissions show that the mean emission is 465462.96 tons, the year with the highest average emissions was 1988 with 812500.00 tons of substances emitted and the lowest average was 2014 with 242500.00 tons of substances emitted.

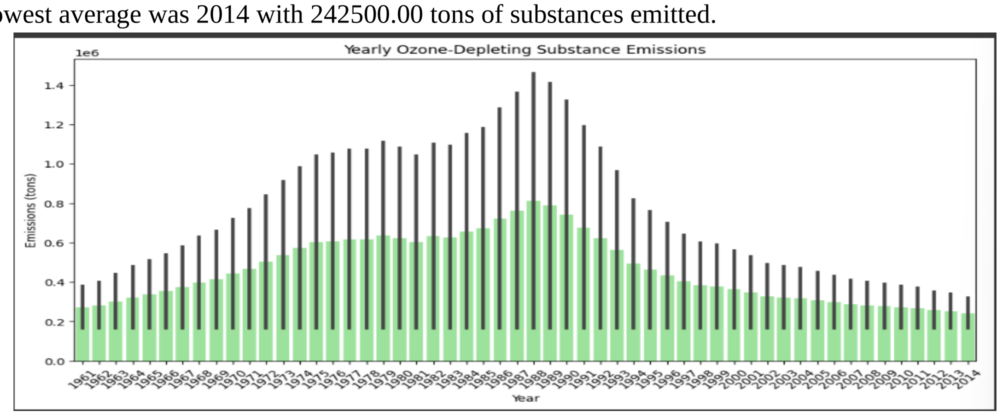

Figure. 3 Emission Peaks in the 1980s.

Over the years Entity with the highest consumption of Methyl Chloroform(TCA) and Methyl Bromide(MB)was The United States, for Hydrochlorofluorocarbons (HCFCs) and Halons it was Asia and for Carbon Tetrachloride (CTC) and Chlorofluorocarbons (CFCs) it was China and Europe respectively. The overall lowest consumption of the substances TCA, MB, HCFCS, CTC, Halons, and CFCs is Afghanistan, Ukraine, Niue, United States, Africa, and Vatican Respectively. And the correlation metrics highly suggest that over the years consumption between Methyl Chloroform and Chlorofluorocarbons (CFCs) are highly correlated. Parties Involved in environmental agreements records over the years 1971-2015 when consolidated collectively provide insights into the global landscape of agreements, participation over time, and their relationship which can be then used for identifying potential collaborations or making efforts on agreements where the participation was noticed to be comparatively lower than others. Considering the analysis done the agreement with the highest parties was the World Heritage Convention with 5321 parties and that with lowest parties and participation was the Rotterdam Convention with 1691 parties, It was noticed that there was the steepest increase in participation with the World Heritage Convention which was 30374 parties and the steepest decrease was with Kyoto Protocol with a decrease of -2832 parties.

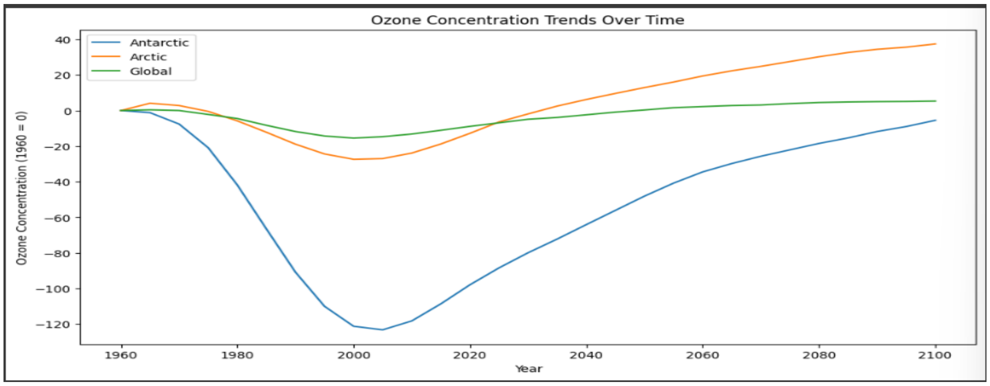

Figure. 4 Stratospheric Ozone Concentration Projections

Figure. 4 visually represents projected changes over time since 1960 quantifying ozone depletion, highlighting the critical periods where significant changes occurred, and comparing trends over the years and projection scenarios where noticed mean, maximum, and minimum ozone concentration occurred was -16.97 unit, 37.40 unit(in 2100) and -123.20 unit (in 2005) respectively which are also plotted region wise (Antarctic, Artic, and Global) for detailed understanding considering regions.

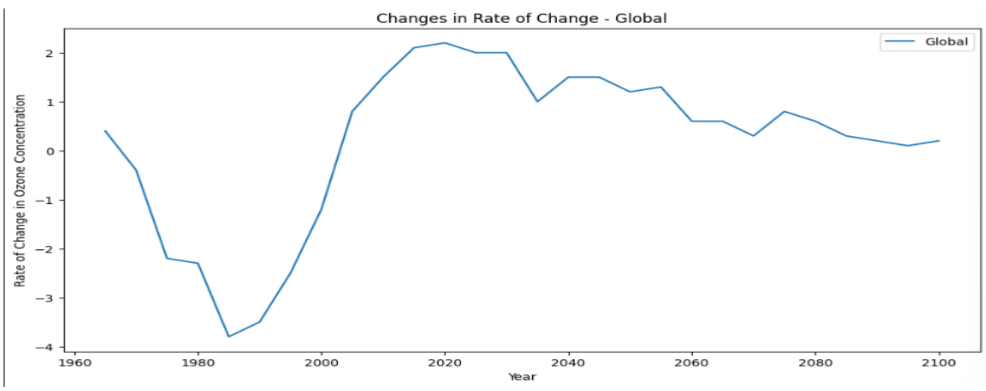

Figure. 5 Change in Rate of Ozone Concentration

Global insights provide that the year with Maximum change was in 2020 as seen in Figure. 5

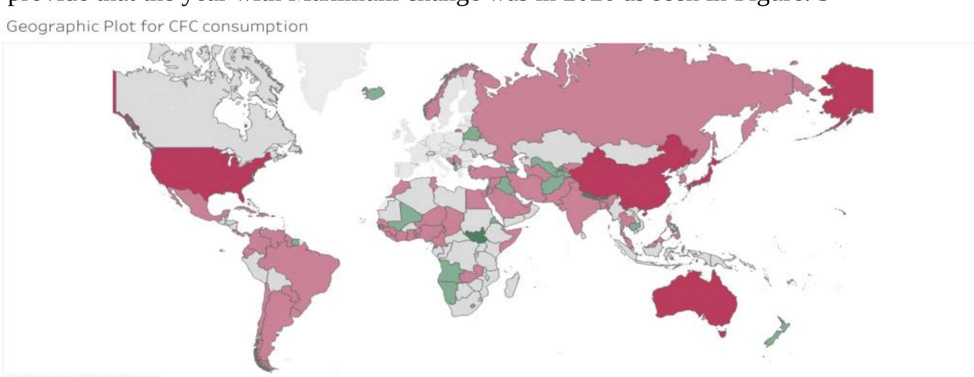

Figure. 6: The Geographic plot for CFC consumption

Finally, Figure. 6 is valuable for understanding the distribution of the CFC emissions globally on a wider range and when this is integrated into game-theory models it will enhance the analysis as well as the strategic interactions and decision-making process amongst the stakeholders.

3.2 Time series Forecasting for Ozone Layer Depletion and Air Quality Index Forecasting

The proposed methodology used SARIMA (Seasonal Autoregressive Integrated Moving Average), ARIMA (AutoRegressive Integrated Moving Average), and Exponential Smoothing for forecasting. SARIMA is a powerful technique used for time series forecasting, particularly when the data exhibits seasonal patterns. It extends the ARIMA (Autoregressive Integrated Moving Average) model to include seasonal components. The SARIMA model is defined by three main components all of which are satisfied by Ozone Layer Depletion Data:

- Seasonal Component (S): Represents the seasonal effect in the data at a specific lag.
- Autoregressive Component (AR): Represents the relationship between an observation and a number of lagged observations.
- Moving Average Component (MA): Represents the error of the model as a linear combination of error terms from previous time points.

The SARIMA model is expressed as:

$$(1-\phi_1 L-\phi_2 L^2-\ldots\ldots-\phi_p L^p)(1-\Phi_1 L^s-\Phi_2 L^{2s}-\ldots\ldots-\Phi_P L^{Ps})(1-L)^d y_t=(1+\theta_1 L+\theta_2 L^2+\ldots\ldots+\theta_q L^q)(1+\Theta_1 L^s+\Theta_2 L^{2s}+\ldots\ldots+\Theta_Q L^{Qs})\epsilon_t$$

Eq. 1

where:

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

SARIMA modeling involves identifying the appropriate values for p , d , q , P, D, and Q through techniques like autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, and then fitting the model to the data to make forecasts.

ARIMA (AutoRegressive Integrated Moving Average) is a popular and powerful technique used for time series forecasting. It models the next step in the sequence as a linear function of the differenced observations, errors, and lags of the series. The ARIMA model is specified by three parameters: p, d, and q.

- AutoRegressive (AR) term (p): It refers to the number of lagged observations included in the model. It captures the effect of previous values on the current value.

- Integrated (I) term (d): It represents the number of differences needed to make the series stationary. It accounts for trends in the data.

- Moving Average (MA) term (q): It denotes the number of lagged forecast errors in the prediction equation. It helps in modeling the error term.

The ARIMA model can be expressed as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_p + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$
Eq. 2

where Y_t is the value at time t, c is a constant, $\phi_1, \phi_2, \ldots \phi_p$ are the AR parameters, $\theta_1, \theta_2 \ldots, \theta_q$ are the MA parameters, ε_t is the error term at time t, and p, d, and q are the order parameters of the model.

Exponential smoothing is a popular technique used in time series forecasting to predict future data points based on past observations. It assigns exponentially decreasing weights to older data points, giving more importance to recent observations. The basic exponential smoothing equation is:

$$y_{new_{t+1}} = \alpha y_t + (1 - \alpha)\text{y\_forecast}$$
Eq. 3

where:

- $y_{new_{t+1}}$ is the forecast for the next time period t+1,
- y_t is the actual observation at time t ,
- y_forecast is the forecast for time t ,
- α is the smoothing parameter ($0 < \alpha < 1$).

This method is simple yet effective, providing forecasts that adapt quickly to changes in the data.

3.3 Game Theory Integration

The authors developed a program to generate custom reports based on stakeholder data requirements. Whenever a user requests a report, the program dynamically creates a report by calling predefined functions. Additionally, the program includes details about suggested protocols based on entered keywords. These protocols include the Montreal Protocol, which is a global agreement aimed at phasing out ozone-depleting substances (ODS) like chlorofluorocarbons (CFCs) and halons. The Vienna Convention for the Protection of the Ozone Layer serves as a framework agreement for international cooperation to protect the ozone layer, setting the stage for the Montreal Protocol. The Copenhagen Amendments strengthen commitments by enhancing control measures and accelerating phase-out schedules in response to evolving scientific understanding. The Beijing Amendment focuses on phasing out hydrochlorofluorocarbons (HCFCs), which are both ODS and potent greenhouse gasses. Lastly, the Kigali Amendment aims to reduce the consumption of hydrofluorocarbons (HFCs), which are potent greenhouse gases, as alternatives to ODS.

Table 1. Protocols by Year

Sr.No	Protocol	Year
1.	The Vienna Convention for the Protection of the Ozone Layer	1985
2.	Montreal Protocol	1987
3.	The Copenhagen Amendments	1992
4.	The Beijing Amendment	1999
5.	The Kigali Amendment	2016

When discussing ozone protection policy, the term "Nash Equilibrium" describes a situation in which all parties participating in the decision-making process select a course of action that, in light of the tactics selected by others, maximizes their own benefits. This idea is especially important when there are several parties engaged, each with their own interests and goals, such as governments, businesses, and environmental organizations.Imagine, for instance, that nations are negotiating a global accord to cut back on emissions of chemicals that deplete the ozone layer. Every nation must choose how much of an effort to make in order to reduce emissions, weighing the advantages of ozone protection against the implementation costs. In the event that no nation can unilaterally alter its approach for reducing emissions while taking into account the tactics adopted by other nations, Nash Equilibrium would result. When it comes to developing strategies that are resilient against prospective actions by other stakeholders, policymakers may foresee the likely results of their decisions with the aid of a knowledge of Nash Equilibrium. It may also help in the negotiation and creation of successful policies by highlighting possible points of disagreement or collaboration between stakeholders.

3.4 Nash Equilibrium

Nash Equilibrium can be used to study ozone layer depletion by examining the strategic interactions of countries and stakeholders in environmental policies. Policymakers can use Nash Equilibrium to determine stable outcomes in which each entity's ozone protection measures are optimal in relation to the actions of others. Understanding the incentives and behaviors of diverse actors allows policymakers to create legislation and international agreements that successfully promote collective action to combat ozone depletion. Nash Equilibrium provides insights into the strategic dynamics of environmental decision-making, allowing for the creation of long-term solutions that balance the interests of all parties involved in the preservation of the ozone layer.

Input:

- Set of players P = {p1, p2, ..., pn}
- Set of strategies for each player S = {S1, S2, ..., Sn}

Output:

- Nash equilibrium strategies

```
1. Initialize equilibriumFound to false
2. while equilibriumFound is false:
3.     for each player pi in P:
4.         Calculate the payoff for each strategy Si in S
5.     end for
6.     for each player pi in P:
7.         Determine if pi has a strategy Si that gives a higher payoff than current strategy
```

8. If yes, update pi's strategy to Si
9. end for
10. Check if all players have strategies that give them maximum payoff
11. If yes, set equilibriumFound to true
12. end while
13. Return the strategies for each player at equilibrium

3.5 Pareto Efficiency:

Policymakers attempt to create legislation and accords that attain Pareto efficiency, which means that no country can improve its environmental condition without hurting another's. This necessitates devising solutions that balance the interests of various nations and groups. International treaties, such as the Montreal Protocol, which attempted to phase out ozone-depleting compounds, are examples of efforts to attain Pareto efficiency by coordinating worldwide action to maintain the ozone layer without excessively burdening any one country. Algorithm: Pareto Efficiency

Inputs:
- 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^*

1. Define Decision Variables:
   Let x_i represent the decision variable for each player i in a strategic interaction.
2. Formulate Utility Functions:
   Define the utility function U_i(x_1, x_2, ..., x_n) for each player i, representing their preferences over outcomes.
3. Identify Feasible Outcome Space:
   Define the feasible outcome space X as the set of all possible combinations of decision variables that satisfy constraints.
4. Find Pareto Optimal Solutions:
   For each solution x* in the feasible outcome space X:
      a. Evaluate the utility U_i(x*) for each player i.
      b. Check if there exists another feasible solution x' such that:
         - U_i(x') ≥ U_i(x*) for all players i, and
         - U_j(x') > U_j(x*) for at least one player j.
      c. If no such solution x' exists, then x* is a Pareto optimal solution.
5. Output Pareto Optimal Solutions:
   Return the set of Pareto optimal solutions x^*.

3.6 Stackelberg Leadership:

Stackelberg Leadership is a game theory strategy in which one player (the leader) decides on a course of action before the other players (the followers) do. In the context of ozone layer depletion, major governments or organizations can establish ambitious emission reduction objectives or invest in cutting-edge ozone protection technologies. This proactive strategy may persuade other countries to follow suit, as they monitor the leader's activities and adapt their strategies accordingly. Stackelberg Leadership may inspire global cooperation and speed efforts to combat ozone depletion, resulting in a more sustainable future.
Algorithm: Stackelberg Leadership

Inputs:
- 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

1. Define Leader and Followers:
   Designate one player as the leader and the rest as followers in a sequential decision-making process.
2. Leader Commits to Strategy:
   Specify the leader's commitment by choosing a strategy s_L.
3. Followers Respond to Leader's Strategy:
   For each follower i:
     a. Observe the leader's chosen strategy s_L.
     b. Choose their own strategy s_i to maximize their payoff given s_L and their own preferences.
4. Leader Anticipates Followers' Responses:
   Anticipate how followers will respond to the leader's chosen strategy s_L.
5. Determine Optimal Strategy for the Leader:
   Evaluate the resulting outcomes to determine the effectiveness of the leader's strategy in influencing follower behavior and achieving the leader's objectives.
6. Output Optimal Strategy for the Leader:
   Return the leader's chosen strategy s_L that maximizes the leader's payoff given the anticipated responses of the followers.

4. RESULTS

Forecasted Ozone Hole Area and Minimum Ozone using ARIMA

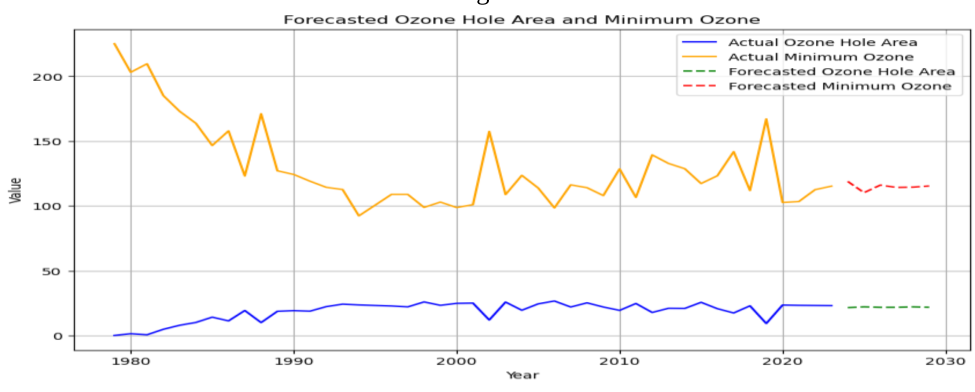

Figure. 7 Forecasting Output ARIMA

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.

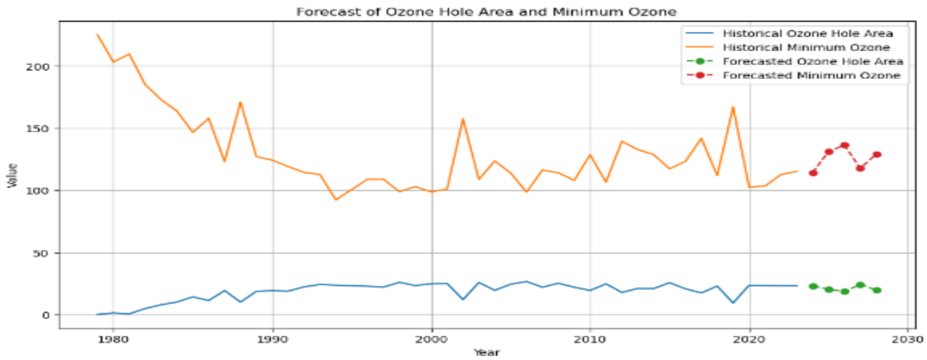

Figure.8 Forecasting output Exponential Smoothing

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 smoothing models 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 difficult to set up, and additional data could be needed for precise predictions.

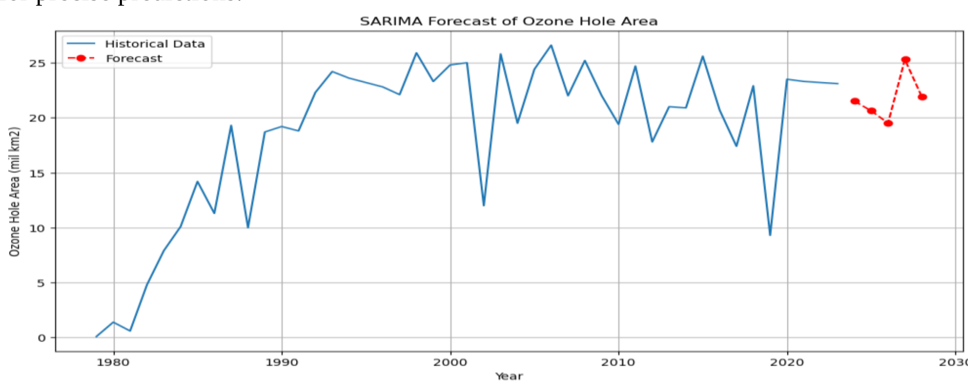

Figure. 9 Forecasted Ozone Hole Area using SARIMA

Table 2. Results

Model	Metric	Value
ARIMA	Mean Absolute Error	4.056
	Mean Squared Error	25.454
	Root Mean Squared Error	5.045
Exponential Smoothing	Mean Absolute Error	5.19
	Mean Squared Error	46.399
	Root Mean Squared Error	6.81
SARIMA	Mean Absolute Error	8.16

Mean Squared Error	83.93
Root Mean Squared Error	9.16

4.1 Accuracy Measures:

Mean Absolute Error:

MAE is derived by averaging the absolute discrepancies between projected and actual values.[18]

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}) \qquad \text{eq-4}$$

Mean Squared Error:

MSE is derived by averaging the squared discrepancies between anticipated and actual values.[18]

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y})^2 \qquad \text{eq-5}$$

Root Mean Squared Error:

Its simply the squared root of MSE.[18]

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y})^2} \qquad \text{eq-6}$$

where, yi = actual value , $\hat{y}$=predicted value ,n= sample size

4.2 Air Quality Index Analysis

The authors performed feature importance, gradient boosting[19] and on applying Decision Tree Classifier [20]the accuracies for training and evaluation were both around 82%.Because it can recognize intricate links in the data and base choices on several criteria, a decision tree may get 82% accuracy. Decision trees are able to catch complicated patterns in the data that linear models can overlook because they can simulate non-linear connections between characteristics and the target variable.

Table 3. Model Results

Model	Accuracy	Value
Decision Tree Classifier	Train	82.919
	Test	82.910

The study in [16] used Air Quality Indices as a tracer for atmospheric stability. Major pollutants are are particulate matter (PM2.5 and PM 10), sulfur dioxide (SO2), nitrogen dioxide (NO2), ozone (O3), carbon monoxide (CO), ammonia (NH3). [17] Of the gasses listed, sulfur dioxide (SO2), nitrogen dioxide (NO2), and carbon monoxide (CO) are not greenhouse gasses, while ozone (O3) and ammonia (NH3) are considered greenhouse gasses and directly affect the ozone layer.

5. DISCUSSION

Air pollution contributes to the depletion of the ozone layer by releasing ODS into the atmosphere, especially from human activities including traffic, industrial operations, and agriculture. Halons, hydrochlorofluorocarbons (HCFCs), and chlorofluorocarbons (CFCs) are some of these chemicals. These substances have the ability to enter the stratosphere after being released, where they interact with ozone molecules to cause ozone depletion. The needs for predicting and the properties of the data determine which technique is best. Because ARIMA models may capture both trend and seasonality in the data, they may outperform SARIMA and Exponential Smoothing in some situations. When there are obvious seasonal patterns in the data, SARIMA is the better option; when there aren't any, Exponential Smoothing works better. The 82% accuracy rate of decision trees can be attributed to their capacity to manage intricate connections, choose pertinent characteristics, and adjust to various data distributions. Because it offers a framework for analyzing strategic interactions and projecting other people's behaviors, game theory can have a favorable impact on decision making. Making better-informed and well-thought-out judgments is facilitated by its assistance in comprehending the effects of various options, maximizing results, and creating tactics that take other participants' conduct into consideration. Ozone layer depletion can be reduced significantly with increasing public awareness.

6. CONCLUSION

To improve estimates of ozone layer depletion, this study concludes with the recommendation of an interdisciplinary approach. The authors want to create a more complete and realistic model by combining game theory, correlation with the Air Quality Index, and ARIMA Time Series forecasting. The findings show encouraging prediction rates and provide guidance for more informed environmental sustainability decision-making. The discoveries made from this multidisciplinary approach could be useful for future study, international collaboration, and policymaking for safeguarding the ozone layer and environmental health.

6.1 **Future work**

Future works can focus on maintaining research and development activities to enhance ozone layer depletion forecasting models by taking trend, seasonality, and the effects of various substances into account.On the basis of empirical data and projection models, push for stricter national and international laws and regulations to preserve the ozone layer.Acknowledge the relationship between ozone layer thinning and climate change, and create adaptation plans that take both problems into account.

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