

**AN ACTION PROJECT TO STUDY AND ANALYZE AIR,  
WATER, AND LAND POLLUTION INDICES FOR A COAL-  
BASED THERMAL POWER PLANT AND TO SUGGEST AI-  
BASED SOLUTIONS FOR FURTHER IMPROVEMENT**

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With Special Reference to  
**Satpura Thermal Power Station, Sarni, District Betul, M.P.**  
Owned & operated by



**Prepared by:**

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## Preface

This study report represents the culmination of a passionate endeavor in environmental research undertaken by Mr. Aditya Mandloi, a final-year secondary education student at The Sanskaar Valley School, Bhopal. Driven by a strong desire to contribute to the field of environmental studies, Mr. Mandloi approached Dr. Nishchol Mishra to pursue this interest.

Under the guidance of Dr. Nishchol Mishra and in collaboration with Mr. Pankaj Pandey, Assistant Professor JNCT Bhopal, Mr. Aditya Mandloi embarked on this significant research project. The team conducted an on-site study at the Satpura Power Plant, located in Sarni, Madhya Pradesh. The primary focus of their investigation was to analyze pollution levels and explore potential interventions using Artificial Intelligence (AI) and Internet of Things (IoT) technologies to mitigate environmental impact.

This report, co-authored by Mr. Aditya Mandloi and Mr. Pankaj Pandey, presents the findings of their research, offering insights into the current environmental challenges faced by the power plant and proposing innovative technological solutions. It stands as a testament to the importance of fostering young talent in environmental science and the potential for cross-generational collaboration in addressing pressing ecological concerns.

The authors would like to express their gratitude to Dr. Nishchol Mishra for his mentorship and to the management of the Satpura Power Plant for their cooperation in facilitating this study. We hope that the findings and recommendations presented herein will contribute meaningfully to the ongoing efforts to balance industrial progress with environmental preservation.

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## Executive Summary

This study provides a comprehensive study of the pollutants emitted by Satpura Thermal Power Plant which has a installed capacity of 1330 MW and is a coal-fired power plant near Sarni in the state of Madhya Pradesh. The study examines the environmental impact in three major domains: air, water, and land. It identifies the main exhaust emissions into each of these areas and provides a comprehensive evaluation of their impact on the environment.

The proposed study investigates the application of Prophet and Auto Regressive Integrated Moving Average (ARIMA) forecasting models for predicting air pollutant emissions at the Satpura Thermal Power Plant in Sarni, Madhya Pradesh, India. The plant's substantial role in regional electricity generation necessitates accurate emission forecasts for effective environmental management.

The study reviews the plant's environmental impact and examines various forecasting methods, with a focus on Prophet and ARIMA. Data from 2019 to 2023 were meticulously preprocessed. The Prophet model achieved a Mean Absolute Error (MAE) of 7.8, providing smooth forecasts and capturing long-term trends. The ARIMA model, with an MAE of 8.67, was effective for short-term fluctuations but less smooth.

The findings suggest Prophet's superior trend forecasting capability, while ARIMA handles short-term variations. Future research should explore hybrid models and additional variables to enhance forecasting accuracy.

In addition, it recommends the utilisation of AI technology in enhancing the pollution control processes in the Satpura plant. It explains the technologies that apply Artificial Intelligence to manage facilities for optimal operation and, at the same time, reduce emissions and waste. It also discusses the application of AI in aspects such as prognostication of maintenance, combustion, and productivity improvement that brings the plant's structure in harmony with contemporary environmental standards and still provides electricity to the people of Madhya Pradesh.

Therefore knowing the facts and consequences of the present day polluting measures and to think long-term about the structure and integrity of the Satpura Thermal Power Plant to meet the energy needs without disrupting the ecological equilibrium is the rationale behind using this integrated technique.

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## Introduction

Thermal power plants that primarily use coal for generation are important in satisfying people's ever-increasing energy needs globally. They are attributed to contributing a reasonable share of the electric power in many nations, including India as well as China. But, though these plants are useful for energy security, they are the main source of the air pollution. They release out gases that hence affect the quality of air, water and soil hence causing environmental/health risks. This report identifies the types of pollution emanating from the Sarni thermal power plant, discusses the effects of these pollutants on the environment and looks at how AI can be utilised to design new innovations to reduce the emissions and their impacts. These plants are also a major source of environmental pollution. They release pollutants that affect air, water, and land, causing widespread ecological damage and health issues.

Situated in Sarni, Madhya Pradesh, India, the Satpura Thermal Power Plant is a cornerstone of the region's electricity generation infrastructure. With an impressive installed capacity of 1330 Megawatts (MW), it significantly contributes to the electrical supply of the surrounding communities.

### Satpura Thermal Power Station, Sarni :

LOCATION	18 K.M. FROM GHORA DONGRI RAILWAY - STATION DIST –BETUL
CAPACITY	1330 M.W.
SOURCE OF WATER	TAWA DAM; LAKE AREA 2893 ACRE
FUEL	PRIMARY FUEL -COAL
	SECONDARY FUEL –FURNACE OIL/HSD
COAL SOURCE	WESTERN COAL FIELD LIMITED
COAL AREA	PATHAKHEDA, KANHAN, PENCH, NAGPUR, CHANDRAPUR, WANI
MODE OF TRANSPORT	RAIL /ROAD/BELT
COAL LINKAGE	79.2 LMT (appx.) PER ANNUM (2007-08)
POWER EVACUATION 400 K.V. LINES	STP – ITARSI/ INDORE
	STP – KORADI/ BHILAI
220 K.V. LINES	STP – ITARSI (4)
	STP - KALMESHWAR (1)

UNITS	CAPACITY MW	COMMISSIONING DATES	MAKE TG SET	MAKE BOILER
Unit I	62.5	DECOMMISSIONING ON 07-01-2014	GE USA	B&W
Unit II	62.5	DECOMMISSIONING ON 05-12-2013	GE USA	B&W
Unit III	62.5	DECOMMISSIONING ON 01-10-2012	GE USA	B&W
Unit IV	62.5	DECOMMISSIONING ON 05-12-2013	GE USA	B&W
Unit V	62.5	DECOMMISSIONING ON 01-02-2013	GE USA	B&W
Unit VI	200	27-06-1979	BHEL	BHEL
Unit VII	210	20-09-1980	BHEL	BHEL
Unit VIII	210	25-01-1983	BHEL	BHEL
Unit IX	210	27-02-1984	BHEL	BHEL
Unit X	250	18-08-2013	BHEL	BHEL
Unit XI	250	16-03-2014	BHEL	BHEL

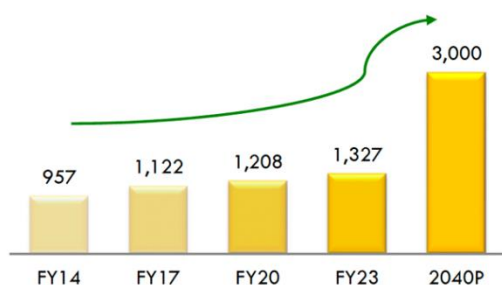
## Strong Growth Drivers for Power Sector in India



### Demand

- India's GDP is expected to grow significantly on the back of our **demographic strength** and India becoming a **Manufacturing Hub**
- India has low per capita consumption of electricity which is expected to rise to 3,000 kWh by 2040

#### Increasing Per Capita Consumption (kWh/Year)



### Supply

- Electricity requirement in India is expected to grow in tandem with GDP growth
- Both peak load demand and energy requirement are expected to rise at a healthy pace

#### Projected Energy requirement & Peak Load (GW)

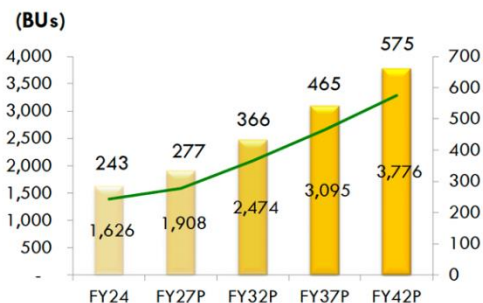
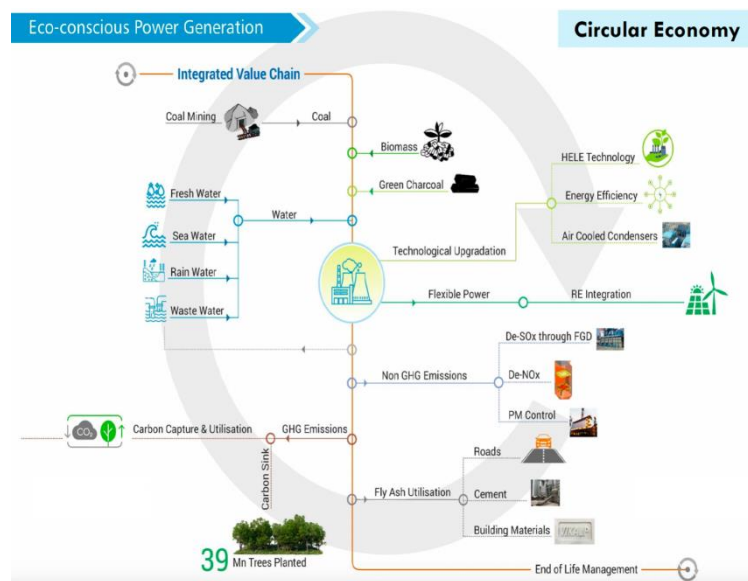


Figure 1: Data & Infographic Courtesy: NTPC Annual Report 2023

## Scope of present Study:

This report explores the role of Artificial Intelligence (AI) in reducing pollution from thermal power plants. Thermal power plants are significant contributors to air pollution, emitting large amounts of carbon dioxide (CO<sub>2</sub>), sulfur dioxide (SO<sub>2</sub>), nitrogen oxides (NO<sub>x</sub>), and particulate matter. AI offers innovative tools to optimize operations, improve energy efficiency, and reduce emissions, providing a more sustainable approach to energy production.

Key AI-driven solutions include predictive analytics for optimizing combustion processes and reducing fuel consumption. AI algorithms can forecast equipment maintenance needs, minimizing unplanned downtime and ensuring more efficient plant operation. Machine learning models can analyze vast datasets to monitor and control emissions in real-time, enabling plants to meet regulatory standards more effectively. Additionally, AI can help integrate renewable energy sources into the grid, reducing reliance on fossil fuels.



**Figure 2: Data & Infographic Courtesy: NTPC Annual Report 2023**

By using AI to enhance decision-making, thermal power plants can automate pollution control mechanisms, optimize resource usage, and implement dynamic adjustments in energy output. This report outlines how AI technologies, when combined with existing pollution control systems, can significantly mitigate the environmental impact of thermal power generation. The goal is to demonstrate how AI can be a game-changer in making thermal energy production cleaner and more efficient.

## Air Pollution: The Largest Contributors

- I. Air pollution from thermal power plants is a major environmental concern due to the significant emissions generated during electricity production. These plants primarily rely on the combustion of fossil fuels such as coal, natural gas, and oil, releasing harmful pollutants into the atmosphere. The primary pollutants emitted include carbon dioxide (CO<sub>2</sub>), sulfur



dioxide (SO<sub>2</sub>), nitrogen oxides (NO<sub>x</sub>), and particulate matter (PM), all of which have detrimental effects on both the environment and human health.

- II. **Carbon dioxide (CO<sub>2</sub>)** is the most prevalent greenhouse gas emitted by thermal power plants, contributing to global warming and climate change. The burning of fossil fuels in these plants is responsible for a significant portion of global CO<sub>2</sub> emissions, making them a key target for climate mitigation efforts.
- III. **Sulfur dioxide (SO<sub>2</sub>)** and **nitrogen oxides (NO<sub>x</sub>)** are major contributors to acid rain, which damages ecosystems, soil quality, and water sources. Additionally, NO<sub>x</sub> reacts with other chemicals in the atmosphere to form ground-level ozone (smog), which causes respiratory problems and exacerbates conditions like asthma and bronchitis.
- IV. **Particulate matter (PM)**, including fine particles like ash and soot, can penetrate deep into the lungs when inhaled, leading to serious health issues such as heart disease, lung cancer, and reduced lung function. Particulate pollution from power plants is particularly harmful to vulnerable populations, including children and the elderly.
- V. Thermal power plants are also a significant source of **mercury emissions**, which accumulate in water bodies and enter the food chain, posing a risk to wildlife and humans.
- VI. Efforts to reduce air pollution from thermal power plants focus on improving combustion efficiency, adopting cleaner technologies, and using pollution control devices such as flue gas desulfurization (FGD), selective catalytic reduction (SCR), and electrostatic precipitators (ESP). Additionally, transitioning to renewable energy sources and using AI for real-time emissions monitoring offer promising solutions to minimize the environmental impact of these plants.

The Satpura Thermal Power Plant has the most significant environmental challenge in the form of air pollution.

In terms of controlling air pollution, the Satpura Thermal Power Plant in Sarni, which has an installed capacity of 1330 megawatts, is confronted with severe obstacles. As a facility that runs on coal, it makes a significant contribution to the emissions that are released into the atmosphere in the Madhya Pradesh region.



## Mitigating Air Pollution:

In order to solve these issues, the Madhya Pradesh Power Generating Company Limited (MPPGCL), which is in charge of operating the Satpura facility, has deployed a number of different pollution control techniques. Among these are electrostatic precipitators, which are used to regulate particulate matter, and designs for flue gas desulfurization units, which are intended to limit emissions of sulphur dioxide. A further enhancement of these efforts might be achieved through the possible installation of technology powered by artificial intelligence, which would optimise combustion processes and reduce overall emissions from the facility.

Types of Pollutant	Impact
<b>Carbon Dioxide (CO<sub>2</sub>)</b>	The Satpura facility is a significant contributor to the state of Madhya Pradesh's carbon monoxide emissions due to the coal combustion technique that it uses. These emissions are important contributors to India's overall greenhouse gas output, which in turn has an impact on climate patterns on both a local and global scale. Because it is one of the bigger thermal power plants in the state, the plant has a particularly substantial impact on the quantities of carbon dioxide produced by the atmosphere.
<b>Sulphur Dioxide (SO<sub>2</sub>)</b>	The emissions of Sulphur dioxide (SO <sub>2</sub> ) from the Satpura facility are a significant obstacle for the quality of the air in Sarni and the districts surrounding it. The local coal that is used in the plant may contain different quantities of Sulphur, which might have an effect on the amount of Sulphur dioxide that is produced. Not only can this pollutant have an effect on the immediate vicinity, but it also contributes to more widespread environmental problems such as acid rain, which can have an effect on the various ecosystems that are found in the Satpura range as well as the water bodies that are located nearby.
<b>Nitrogen Oxides (NO<sub>x</sub>)</b>	The Satpura facility is responsible for the emission of particulate matter, which includes fly ash and other relatively tiny particles, in addition to gaseous pollutants. These emissions have the potential to have direct health repercussions on the people living in Sarni and the villages that surround it, in addition to contributing to respiratory and cardiovascular problems.
<b>Particulate Matter</b>	The Satpura facility is responsible for the emission of particulate matter, which includes fly ash and other relatively tiny particles, in addition to gaseous pollutants. These emissions have the potential to have direct health repercussions on the people living in Sarni and the villages that surround it, in addition to contributing to respiratory and cardiovascular problems.



Figure 3: Team discussion with technical heads and experts on site

### Water Pollution:

Water pollution caused by thermal power plants is a significant environmental issue. These plants rely heavily on water for cooling and steam generation, often drawing large volumes from nearby water bodies. The primary sources of water pollution from thermal power plants include **thermal pollution**, **discharge of chemicals**, and **heavy metals**.

**Thermal pollution** occurs when heated water used for cooling is discharged back into rivers, lakes, or oceans. This sudden rise in water temperature can disrupt aquatic ecosystems, reducing oxygen levels and harming marine life. Fish, plants, and other organisms may die or migrate due to the drastic temperature changes.

In addition to thermal pollution, **chemical pollutants** such as chlorine (used in cooling systems to prevent biological growth), oil, and grease can be released into water bodies. **Heavy metals** like mercury, arsenic, and lead, which are present in the fly ash and waste products from coal combustion, can leach into groundwater or surface water. These contaminants pose severe risks to human health and wildlife.

Efforts to mitigate water pollution include **wastewater treatment systems**, using **closed-loop cooling systems**, and adopting **cleaner energy technologies**. By implementing such measures, thermal power plants can reduce their impact on water resources and protect aquatic ecosystems.

Due to the emission of harmful byproducts like coal ash and heavy metals, the Satpura Thermal Power Plant in Madhya Pradesh, India, considerably adds to the water pollution in the areas around it.

**a. Coal Ash:**

Arsenic, mercury, lead, and other heavy metals are found in coal ash, which is a waste result of burning coal at the Satpura plant. If this coal ash is not thrown away properly, it can leak into nearby bodies of water and possibly pollute the Tawa River and freshwater sources nearby. Fish and other watery animals in the area have died because these poisonous substances are very bad for the aquatic ecosystems in the area. People in the area who depend on these water sources or eat fish that comes from contaminated waters may also have major health problems, such as higher risks of cancer and neurological disorders.

**b. Thermal Pollution:**

Large amounts of water are needed for cooling the Satpura Thermal Power Plant, probably derived from the adjacent Tawa River or reservoir. Often used water is dumped back into the river at a higher temperature following use. This thermal pollution increases the temperature of the Tawa River, therefore influencing the survival of nearby aquatic life sensitive to temperature variations. Higher water temperatures can cause oxygen levels in the river to drop, therefore endangering aquatic life and upsetting the local ecology.

**c. Heavy Metal Contamination:**

Released from the Satpura plant into surrounding water bodies, heavy metals including mercury, lead, and arsenic gather in the local food chain. In the area, this biomagnification process seriously compromises human health as well as that of the local fauna.

Mercury contamination in the Tawa River or other water bodies can lead to mercury poisoning in local populations that consume fish from these sources. This can potentially result in neurological damage and developmental problems in children living in nearby towns.



Figure 4: Team visit at Boiler Station

**d. Land Pollution:**

In spite of the fact that the contamination of the air and water caused by the Satpura Thermal Power Plant is frequently the most obvious indication of environmental deterioration, the pollution of the land is also a big worry in the surrounding area. The improper disposal of coal ash and other solid wastes from the plant has the potential to contaminate the soil in the surrounding area.

It can have profound effects on the environment and the health of the populations that are located in close proximity to the thermal power plant the study was conducted in.

### **Soil Contamination:**

There is a possibility that hazardous compounds will seep into the ground if coal ash from the Satpura factory is disposed of in landfills or open storage pits located in the surrounding area. Because of the presence of these pollutants, which include heavy metals like cadmium, chromium, and lead, the quality of the soil in the area is diminished, and it is no longer suitable for agricultural purposes or the growth of plants. Agricultural communities in Madhya Pradesh, which are located in close proximity to the plant and where farming plays a significant role in the economy of the region, are particularly concerned about this development. Additionally, it is possible that these contaminants will find their way into groundwater, which will significantly exacerbate the problem by putting drinking water supplies in nearby cities and villages at risk.

### **Groundwater Pollution:**

The waste from the Satpura factory has the ability to seep harmful substances into the soil, which has the potential to contaminate the local groundwater. The groundwater is a vital source of drinking water for several villages in the surrounding area. Groundwater is a long-term environmental hazard that poses a threat to the region since it is difficult and expensive to repair after it has gained contamination. There is a possibility that communities that are located in close proximity to the Satpura Thermal Power Plant and rely on groundwater may have health issues as a consequence of their prolonged exposure to these dangerous chemicals.

It is possible that the magnitude of this contamination will have a wide-ranging impact, given that the Satpura facility is one of the major thermal generating stations in the state of Madhya Pradesh. The failure of the plant to design and severely enforce appropriate waste management and soil protection methods may have a significant and long-term impact on the sustainability of the local agricultural sector, as well as on the sources of drinking water and the overall health of the environment.



## Project Objectives



Figure 5 & 6: Team Visit of Boiler & Generator Site

During the site visit to the 2x250 MW Satpura coal-fired thermal power plant, a detailed analysis of pollution indices was conducted, revealing severe environmental impacts on air, water, and land. The study identified significant air pollution from coal combustion, focusing on key pollutants like CO<sub>2</sub>, SO<sub>2</sub>, NO<sub>x</sub>, and particulate matter (PM<sub>10</sub> and PM<sub>2.5</sub>). Emissions regularly exceeded permissible limits, particularly for SO<sub>2</sub> and NO<sub>x</sub>, with the absence of carbon capture technologies worsening the plant's contribution to climate change. Water contamination from cooling discharge, containing toxic heavy metals like lead and mercury, and improper coal ash disposal leading to land pollution were also major concerns.

The study's objective is to

1. Evaluate and compare the application of Prophet and ARIMA models for predicting air pollutant emissions at the Satpura plant.
2. Recommend AI-driven solutions to optimize plant operations, enhance emission controls, and promote sustainability.

By integrating Prophet and ARIMA models for forecasting emissions and utilizing AI-driven methods for environmental monitoring and operational enhancements, this study seeks to improve the Satpura plant's pollution management and promote sustainable practices for a healthier ecosystem.



Figure 7: View of power Substation for evacuation on site

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## Literature Review

The prediction of emissions in thermal power plants is a critical aspect of environmental regulation compliance and the reduction of ecological impacts from power generation. A variety of methodologies, including traditional statistical techniques, machine learning algorithms, and hybrid models, are utilized for this purpose. This review provides an analysis of these methodologies, emphasizing their advantages, limitations, and suitability in various scenarios.

### 3.1 Conventional Statistical Techniques

Conventional statistical techniques, encompassing regression analysis, time-series analysis, and autoregressive integrated moving average (ARIMA) models, have been extensively employed for emission prediction.

**Regression Analysis:** Linear regression models formulate a correlation between emissions and influential factors such as fuel type, load, and ambient conditions. While this method is straightforward and interpretable, it may not effectively capture intricate, non-linear relationships in emission data [10].

**Time-Series Analysis:** Techniques like ARIMA utilize historical emission data to forecast future values. These models are efficient when emissions display consistent patterns over time but may encounter difficulties with irregular or highly variable data [5, 11].

### 3.2 Machine Learning Techniques

Machine learning (ML) techniques have gained traction due to their capacity to manage large datasets and identify complex patterns. Common ML methodologies used in emission prediction include support vector machines (SVM), neural networks, and ensemble methods.

**Support Vector Machines (SVM):** SVM models can manage non-linear relationships by mapping input features to high-dimensional spaces. They have been effectively used for predicting NO<sub>x</sub> and SO<sub>x</sub> emissions, but their performance is heavily reliant on the selection of kernel functions and parameters [1].

**Neural Networks:** Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can model complex, temporal dependencies in emission data. These models necessitate large datasets and significant computational resources but offer high accuracy [1,2,11].

**Ensemble Methods:** Techniques like random forests and gradient boosting machines amalgamate multiple learning algorithms to enhance prediction accuracy. These methods are robust to overfitting and can manage complex interactions between variables [9].

### 3.3 Hybrid Models

Hybrid models amalgamate conventional statistical techniques with machine learning approaches to capitalize on the strengths of both[6].

**Statistical-ML Hybrids:** These models employ statistical methods to preprocess and decompose emission data, followed by ML algorithms for prediction. For instance, a hybrid ARIMA-ANN model can initially use ARIMA to capture linear trends and then apply an artificial neural network (ANN) to model non- linear patterns [7].

**Data Assimilation Techniques:** These methods integrate observational data with model outputs to enhance forecast accuracy. Kalman filters and particle filters are commonly used for real-time emission forecasting in this context [8].

### 3.4 Emerging Methodologies

Recent advancements in artificial intelligence and big data analytics have introduced new methodologies for emission forecasting.

**Deep Reinforcement Learning:** This technique optimizes emission control strategies by learning from interactions with the environment. It is particularly useful for dynamic and complex systems like power plants [5].

**Big Data Analytics:** Leveraging large-scale data from sensors and Internet of Things (IoT) devices, big data analytics can provide real-time insights and improve forecasting models. These methods require advanced data management and processing capabilities [4].

Therefore, the evolution of emission forecasting methodologies in thermal power plants indicates a shift towards more sophisticated, data-driven approaches.

While conventional statistical methods provide a foundation, machine learning and hybrid models offer enhanced accuracy and robustness. Emerging methodologies like deep reinforcement learning and big data analytics hold promise for future advancements. The ongoing research and development in this field aim to enhance the precision and reliability of emission forecasts, contributing to improved environmental management and regulatory compliance.

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## **Methodology**

This project's main objective is to assess the pollution indices of the Satpura Thermal Power Plant, a coal-fired facility located in Madhya Pradesh, India, with a focus on air, water, and land pollution. The study's objectives are to pinpoint the main sources of pollution and calculate the amount of environmental harm the plant's operations have caused. The initiative also focuses on suggesting AI-based solutions to enhance operating procedures, lessen negative environmental effects, and enhance pollution control efforts. The suggestions will assist the Satpura plant in better adhering to national authorities' and the Madhya Pradesh Pollution Control Board's environmental guidelines.

### **4.1 Data Collection and preprocessing**

The success of machine learning in emission forecasting depends heavily on data quality and comprehensiveness. Key data types include operational data (unit-level information on fuel, electricity generation, plant load, operating parameters, and maintenance), emission data (from Continuous Emission Monitoring Systems and stack sampling), and environmental data (ambient air quality and meteorological conditions). Data preprocessing is crucial, involving handling missing values, outlier detection, and normalization. The project uses emission data from 2019 to 2023 sourced from the Madhya Pradesh Pollution Control Board portal(MPPCB) and Satpura Thermal Power Plant(STPP), which underwent preprocessing to address missing values (particularly during site shutdowns), handle outliers, and scale the data appropriately. This thorough data preparation ensures a robust foundation for accurate emission forecasting at the Satpura Thermal Power Plant.

### **4.2 Machine Learning model**

This section explores the use of Prophet and ARIMA(Auto Regressive Integrated Moving Average) machine learning algorithms, for forecasting emissions at the Satpura Thermal Power Plant. Prophet is an open-source machine learning model designed for time series forecasting. It excels in handling data with strong seasonality. Prophet employs an additive model that breaks down time series into trend, seasonality, holidays, and error components.

On the other hand, the ARIMA model analyzes historical power plant emission data to predict future levels. They account for seasonal patterns, long-term trends, and short-term fluctuations in plant operations. This forecasting helps operators plan for regulatory compliance, identify equipment issues, implement emission reduction strategies, and optimize plant operations. ARIMA's ability to capture complex patterns makes it valuable for balancing energy production with environmental concerns in power plants.

Moreover, Prophet's non-parametric approach to seasonality and holidays, along with its interpretability, makes it suitable for Power Plant emission forecasting. The proposed algorithm 1 uses Prophet's ability to capture seasonal variations, incorporate holiday effects and provide interpretable results. However, it's important to consider Prophet's limitations, such as its relatively simple model structure and dependence on high-quality training data.



Figure 8: team meeting with plant experts

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# Implementation

## 5.1 Prophet Model Building

The process for the Prophet model begins with **data preparation**, where time-series emission data is cleaned and formatted to include timestamps and corresponding values. Next, the **Prophet model** is initialized, which can be done with default settings or customized to include specific seasonality and holiday effects. Once initialized, the model is **fitted to the historical data**, allowing it to learn and capture trends and seasonal patterns. After fitting, the model is used to **generate forecasts** for future periods, including uncertainty intervals. Finally, the model's performance is **evaluated using metrics** such as Mean Absolute Error (MAE) to assess the accuracy of the forecasts. **Algorithm 1: Predict Emissions With Prophet** mentioned in *Appendix* is devised for forecasting emissions using Prophet in this study.

## 5.2 ARIMA Model

For the ARIMA model, the process starts with **preparing the data** to ensure it is stationary, which may involve differencing the data if needed. Following this, the appropriate parameters for AR (Auto-Regressive), I (Integration), and MA (Moving Average) components are identified using **Autocorrelation Function (ACF)** and **Partial Autocorrelation Function (PACF)** plots. The model is then **fitted to the historical data** using these parameters. After fitting, forecasts for future periods are generated. The performance of the ARIMA model is evaluated using metrics such as MAE to determine its accuracy and effectiveness. **Algorithm 2: ARIMA Time Series Forecasting** mentioned in *Appendix* is devised for forecasting emissions using ARIMA in this study.

## 5.3 Emission Forecast Evaluation Metrics

### Mean Absolute Error (MAE)

Mean Absolute Error (MAE) in time series forecasting is a widely used metric for evaluating the accuracy of predictive models. It measures the **average magnitude of errors** between the predicted and actual values, without considering their direction. MAE is calculated by taking the mean of the absolute differences between the forecasted values and the observed values in the time series.

$$MAE = \frac{1}{n} \sum_{i=1}^n |\text{forecasted}_i - \text{actual}_i|$$

Where:

- $n$  is the number of observations.
- $\text{forecasted}_i$  is the predicted value at time  $i$ .
- $\text{actual}_i$  is the actual value at time  $i$ .



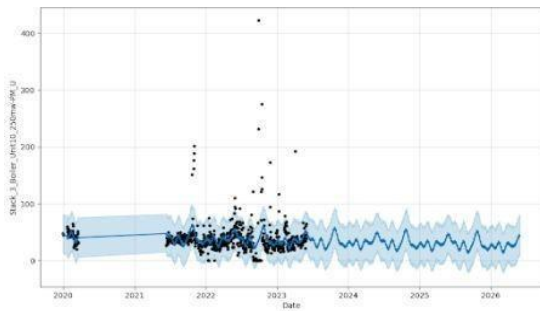
Figure 9 & 10: Plant Economiser & modern control room for emission control

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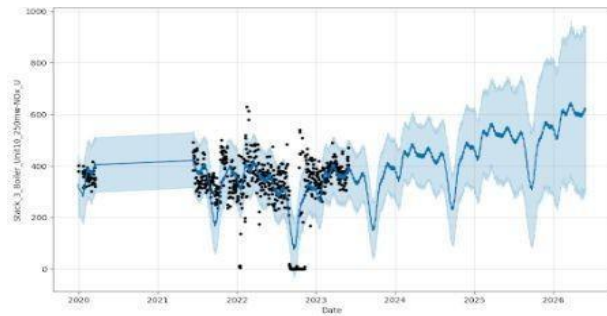


## Result and Discussion

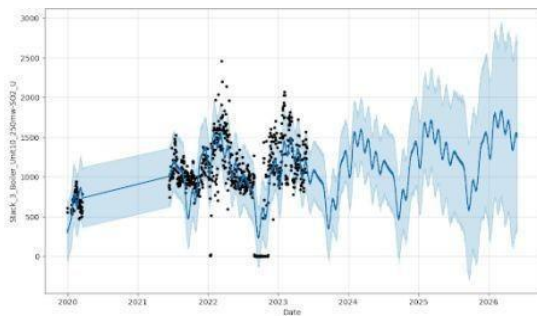
Figure 11 below illustrates the forecast results for various emissions from "Stack 3 Boiler Unit 10" at the Satpura Thermal Power Plant using Algorithm 1 (See Appendix 1) using the Prophet model. The Prophet model, applied within this algorithm, generates smoother forecasts that effectively highlight overall trends, demonstrating upward trajectories in particle matter, sulfur dioxide (SO<sub>2</sub>), nitrogen oxides (NO<sub>x</sub>), carbon monoxide (CO), and carbon dioxide (CO<sub>2</sub>) levels over time. This model also shows increasing uncertainty intervals as the forecast horizon extends, making it particularly valuable for long-term trend prediction and strategic planning at the plant. The forecasts are based on daily data from April 1, 2020, to March 31, 2024—approximately 1,100 days after accounting for holidays and the COVID-19 pandemic. With an MAE of 7.80, the Prophet model is deemed reliable for operational use and supports effective decision-making.



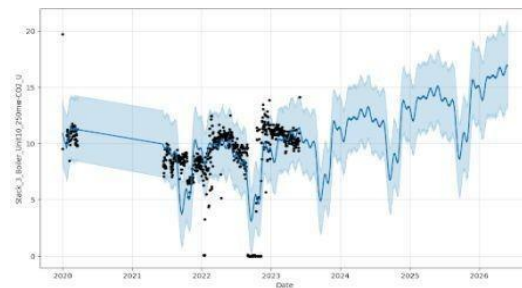
**(a) Particle Matter**



**(b) NOx**

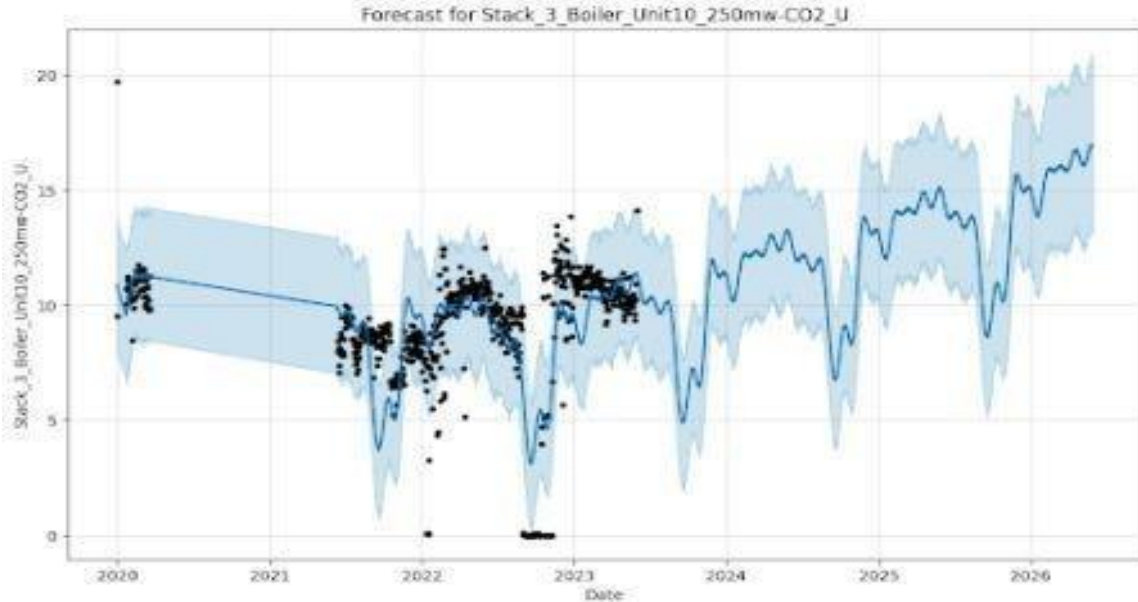


**(c) SO2**



**(d) CO**



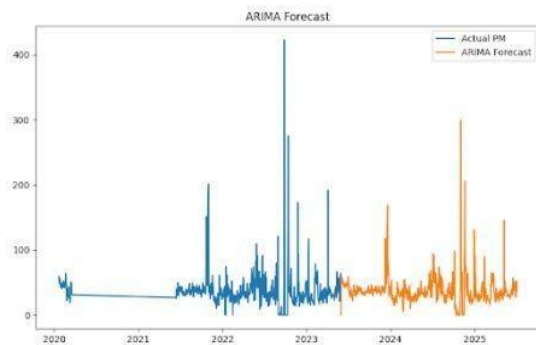


(e) CO<sub>2</sub>

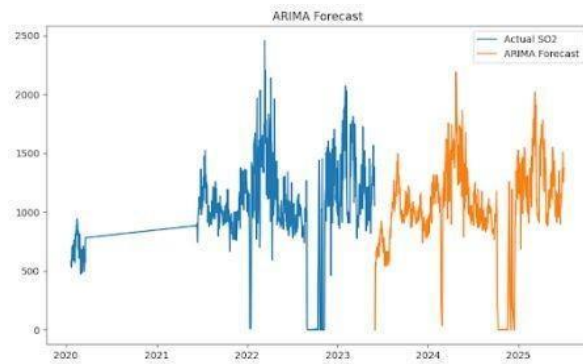
**Figure 11: Prophet Forecast for emissions of Stack 3 Boiler Unit10**

Figure 12 illustrates forecast performance of Prophet and ARIMA for various emissions of Satpura Thermal Power Plant Sarni Madhya Pradesh. Table 1 below gives the Mean Absolute Error (MAE) for Prophet and ARIMA Forecasting Models respectively.

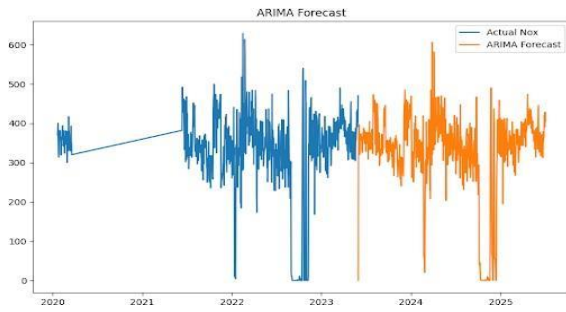
In comparison, the ARIMA (Autoregressive Integrated Moving Average) model, as shown in Figure 13, exhibits more erratic forecasts with an MAE of 8.67. This higher MAE reflects greater variability and less smoothness in the ARIMA predictions. Despite its higher error margin, the ARIMA model provides valuable insights into emissions trends and, when used alongside Prophet, can enhance overall forecasting accuracy and decision-making. Table 1 compares the performance of Prophet and ARIMA forecasting.



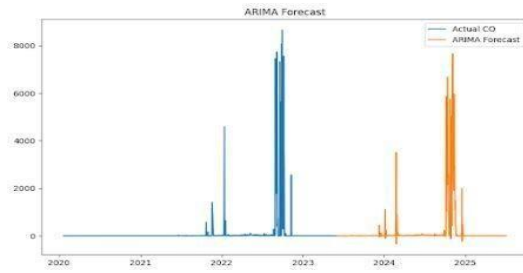
(a) Particle Matter



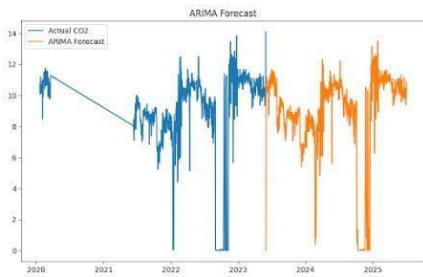
(b) NO<sub>x</sub>



(c) SO<sub>2</sub>



(d) CO

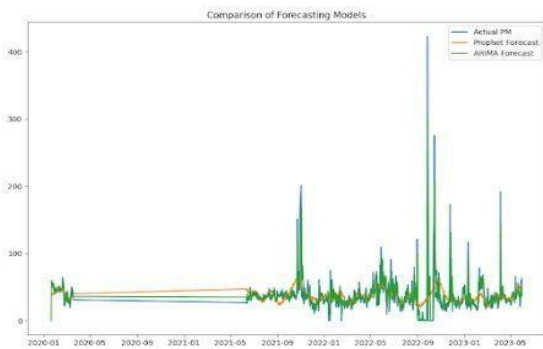


(e) CO<sub>2</sub>

Figure 12: ARIMA Forecast for emissions of Stack 3 Boiler Unit10

Table 1: Mean Absolute Error (MAE) for Forecasting Models

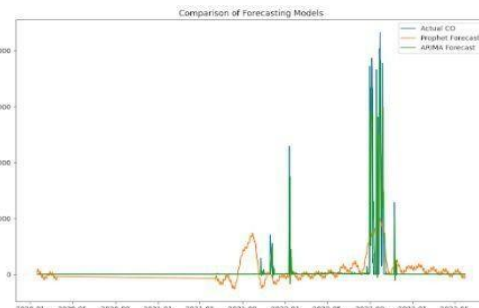
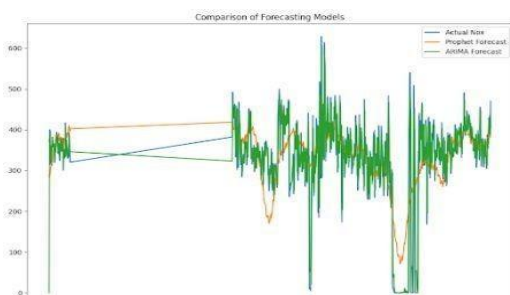
Emission Forecast Model	Mean Absolute Error
Prophet	7.80
ARIMA	8.67



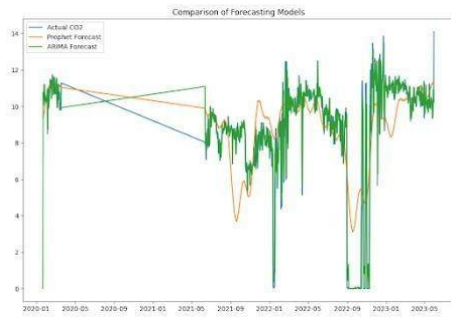
(a) Particle Matter



(b) NO<sub>x</sub>



(c) SO2



(d) CO

(e) CO2

Figure 13: Prophet Vs ARIMA Forecast performance for various emissions

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## **Recommendations**

AI-driven solutions recommended in this section will offer promising opportunities to optimize plant operations, reduce emissions, and enhance environmental sustainability at the Satpura Thermal Power Plant. Like many coal-fired power plants, the Satpura facility faces significant environmental challenges concerning air emissions, water management, and land pollution. By integrating Artificial Intelligence (AI) technologies, the plant can adopt a more sustainable and efficient approach to mitigating its environmental impact. AI-powered solutions, particularly in combustion optimization, water treatment, and ash management, can help minimize harmful emissions and ensure compliance with environmental regulations while maintaining operational efficiency.

### **Air Emissions Control**

#### **Combustion Optimization**

AI helps control air emissions at Satpura Thermal Power Plant by optimizing combustion for CO<sub>2</sub> and SO<sub>2</sub> reduction.

#### **Fuel Burn Rate Optimization**

- AI systems analyze boiler sensor data to adjust feed rates for efficient combustion.
- This reduces CO<sub>2</sub> and unburnt hydrocarbon emissions while improving overall fuel efficiency.

#### **Temperature Control**

- AI monitors and adjusts combustion temperatures to reduce nitrogen oxides (NO<sub>x</sub>) generation.
- This helps the plant meet NO<sub>x</sub> emission regulations while maintaining energy efficiency.

#### **Predictive Algorithms for Emission Control**

##### **Predictive Pollution Control**

- AI analyzes past emission data and operating schedules to forecast emission peaks.
- This allows the plant to adapt operations proactively, such as reducing load during high air pollution periods.

##### **Dynamic Plant Adjustments**

- AI works with real-time monitoring systems to automatically adjust plant operations.
- This helps cut emissions during peak periods while maintaining efficiency.

## Water Management

### AI-Powered Filtration Systems

#### Smart Filtration Systems

- AI optimizes filtration operations by analyzing real-time water quality data.
- The system adjusts factors like pressure and flow rate to better remove toxins such as lead, mercury, and cadmium.

#### Adaptive Filtration

- AI predicts seasonal or operational changes affecting water quality.
- This allows the facility to proactively adapt filtering processes for variable contamination levels.

### Predictive Maintenance of Water Treatment Plants

#### Real-Time Monitoring

- Sensors on key water treatment equipment provide data to AI systems.
- AI analyzes patterns to detect early signs of equipment failure.

#### Failure Prediction

- Machine learning models forecast equipment failures.

This enables timely repairs, minimizing disruptions to the water treatment process and ensuring continuous compliance with water quality regulations. Mitigating air pollution in thermal power plants requires a combination of advanced technologies, cleaner fuels, and regulatory measures aimed at reducing harmful emissions. Since thermal power plants primarily use fossil fuels like coal, oil, and natural gas, their combustion releases pollutants such as carbon dioxide (CO<sub>2</sub>), sulphur dioxide (SO<sub>2</sub>), nitrogen oxides (NO<sub>x</sub>), and particulate matter. Implementing effective strategies is crucial to minimize the environmental and health impacts of these emissions.

#### Key Strategies for Mitigating Air Pollution:

##### 1. Emission Control Technologies:

- **Flue Gas Desulfurization (FGD):** This technology removes sulphur dioxide from the exhaust gases produced by coal-fired power plants. By using scrubbers, FGD can capture up to 90% of SO<sub>2</sub> emissions, reducing the risk of acid rain.
- **Selective Catalytic Reduction (SCR):** SCR systems reduce nitrogen oxide (NO<sub>x</sub>) emissions by converting them into harmless nitrogen and water using a catalyst and ammonia. This process can achieve up to 90% reduction in NO<sub>x</sub> emissions.

- **Electrostatic Precipitators (ESP) and Baghouse Filters:** These devices are designed to remove particulate matter from exhaust gases. They use electric charges or fabric filters to capture and remove fine particles before they can enter the atmosphere.
- 2. **Switching to Cleaner Fuels:**
  - Switching from coal to natural gas can significantly reduce emissions, as natural gas produces fewer pollutants, including lower levels of CO<sub>2</sub>, SO<sub>2</sub>, and NO<sub>x</sub>.
  - Co-firing with biomass, which involves blending coal with plant-based materials, can reduce emissions and offer a more sustainable approach to energy production.
- 3. **Carbon Capture and Storage (CCS):**
  - CCS is an emerging technology designed to capture CO<sub>2</sub> emissions before they are released into the atmosphere and store them underground in geological formations. This method can drastically reduce the carbon footprint of thermal power plants, though it is still in development and requires further investment.
- 4. **Improving Energy Efficiency:**
  - Enhancing the overall efficiency of thermal power plants can reduce the amount of fuel needed to generate electricity, resulting in fewer emissions. This includes upgrading turbines, optimizing combustion processes, and using combined cycle technology.
- 5. **AI and Data Analytics:**
  - AI can play a vital role in monitoring and optimizing power plant operations. Machine learning algorithms can predict maintenance needs, adjust combustion parameters, and ensure emissions remain within legal limits, thereby improving efficiency and reducing pollution.
- 6. **Regulatory Measures:**
  - Governments can enforce stricter emission standards, provide incentives for adopting cleaner technologies, and promote renewable energy integration. Carbon pricing and emission trading systems are additional mechanisms to encourage pollution reduction.

By combining these technologies and approaches, thermal power plants can significantly reduce their environmental footprint while continuing to meet the growing energy demands of society.

## **Land Pollution Management**

### **AI-Driven Ash Management Systems**

#### **a. Forecasting Ash Disposal Needs:**

- AI uses operational data to estimate future ash production and optimize disposal schedules.
- This prevents ash accumulation and reduces the risk of soil contamination.

#### **b. Risk Mitigation for Leaching**

- AI algorithms monitor environmental factors to predict when hazardous compounds from ash are most likely to leach.
- This enables preventive measures, such as covering ash disposal sites or stabilizing ash.

#### Soil Condition Monitoring and Automated Corrective Action

##### a. **Continuous Soil Monitoring**

- Sensors in the soil measure pH, moisture, and pollutant concentrations.
- AI analyzes these signals in real-time to detect any soil pollution.

##### **Automated Corrective Activities**

- When contamination is detected, AI systems automatically initiate actions such as adding neutralizing agents or initiating phytoremediation processes.
- This ensures that land pollution is kept under control.

## **The Future of AI in Environmental Management**

### **Potential Advancements:**

Artificial Intelligence (AI) offers innovative tools for pollution control in thermal power plants, improving efficiency, reducing emissions, and optimizing operations. These tools help monitor emissions in real-time, predict maintenance needs, and automate pollution reduction strategies. Below are key AI-driven tools and applications used to control pollution in thermal power plants?

### **1. Predictive Maintenance Systems**

AI-based predictive maintenance tools analyze data from sensors to predict when equipment is likely to fail or need servicing. Early detection of issues in components like boilers, turbines, and scrubbers ensures that they operate efficiently, reducing energy waste and emissions.

- **Machine Learning (ML) Algorithms:** ML algorithms identify patterns and trends in equipment performance to anticipate failures, minimizing downtime and maintaining optimal efficiency.

### **2. AI-Powered Emission Monitoring**

AI systems can continuously monitor emissions in real-time, identifying any deviation from regulatory limits. These systems can detect pollutants such as SO<sub>2</sub>, NO<sub>x</sub>, CO<sub>2</sub>, and particulate matter (PM) and optimize processes accordingly.



- **Automated Reporting:** AI can generate real-time reports and alerts for plant operators and regulators, ensuring compliance with environmental standards.

### 3. Combustion Optimization

AI-driven systems can optimize the combustion process by adjusting fuel mix, air supply, and combustion conditions in real-time. These adjustments help reduce the formation of pollutants, particularly NOx and particulate matter, by ensuring more complete combustion of fuels.

- **Neural Networks:** Neural networks are used to model complex combustion processes, continuously adjusting inputs to minimize emissions and fuel consumption.

### 4. Energy Efficiency Optimization

AI tools can optimize overall plant performance by monitoring energy production, consumption, and emissions. This involves:

- **Digital Twins:** A digital twin is a virtual model of the power plant that simulates operations. AI algorithms run various scenarios to identify ways to improve energy efficiency and reduce emissions.
- **Adaptive Control Systems:** AI can dynamically adjust power plant parameters to ensure maximum efficiency with minimal emissions.

### 5. Carbon Capture Optimization

AI can enhance carbon capture and storage (CCS) technologies by optimizing the capture process, improving CO2 absorption efficiency, and reducing energy requirements.

- **AI Models for CO2 Capture:** AI models can analyze the performance of carbon capture systems in real-time, optimizing temperature and pressure to capture the maximum amount of CO2 with minimal energy loss.

### 6. Emission Trading and Carbon Credit Management

AI-powered systems can help thermal power plants manage emission trading by predicting their carbon footprint, buying or selling carbon credits, and ensuring compliance with carbon reduction goals.

- **Blockchain and AI:** AI combined with blockchain can provide transparent, real-time tracking of emission reductions, enabling efficient trading of carbon credits.

## 7. AI-Based Flue Gas Treatment

AI algorithms can optimize flue gas treatment systems like electrostatic precipitators and flue gas desulfurization units. These systems remove pollutants from the exhaust gases, and AI ensures they operate at peak efficiency with minimal energy use.

- **Self-Learning Systems:** These systems learn from past performance to fine-tune operational settings, ensuring that pollutant removal is maximized.

## 8. AI-Driven Environmental Impact Assessment

AI can analyze the broader environmental impact of a thermal power plant, helping to model air quality and predict pollution dispersion patterns. This helps operators make informed decisions to mitigate environmental harm.

- **AI for Air Quality Forecasting:** AI models predict the impact of emissions on local and regional air quality, enabling better pollution control strategies.

## 9. AI-Enhanced Data Analytics

AI systems process and analyze large volumes of data from plant operations, environmental sensors, and historical records to identify inefficiencies and recommend improvements. AI enables operators to make data-driven decisions, improving plant performance and reducing emissions. By integrating these AI tools, thermal power plants can achieve significant reductions in pollution, enhance operational efficiency, and ensure compliance with environmental regulations. AI-driven solutions provide a path forward for more sustainable energy production while meeting the growing energy needs.

### Integrated Monitoring Systems

- AI-powered systems integrated with IoT devices can provide more accurate monitoring of air, water, and land conditions.
- This gives the plant a comprehensive view of its environmental impact.

### Advanced Predictive Models

- Continuous improvements to machine learning algorithms will enhance the plant's ability to identify future emission risks and take preventive actions.

### Collaborative AI Systems

- Future AI systems could share environmental data with neighboring industries and plants.
- This would enable a regional approach to pollution management, reducing the overall environmental burden.

## Conclusion

This study found Prophet superior for forecasting air pollutant emissions at the Satpura Thermal Power Plant, with a Mean Absolute Error (MAE) of 7.80 compared to ARIMA's MAE of 8.67. Prophet's effectiveness in handling complex trends and seasonal patterns resulted in more accurate long-term forecasts. ARIMA, while effective in short-term predictions, showed limitations with longer-term forecasts. Combining Prophet and ARIMA in a hybrid model might enhance accuracy. Exploring advanced techniques like LSTM networks could further improve forecasting reliability and precision.

Moreover, this report also provides actionable AI-driven solutions to address the environmental concerns confronting the Satpura Thermal Power Plant. Proposed solutions include optimizing combustion operations for lower CO<sub>2</sub> and SO<sub>2</sub> emissions, upgrading water treatment systems, and improving ash disposal procedures. By using these AI-based solutions, the plant may dramatically minimize its environmental impact, assure regulatory compliance, and establish itself as a pioneer in sustainable energy generation. These methods not only reduce immediate environmental dangers, but also provide long-term ecological advantages to the region.

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## Author Profiles

### **Brief Bio of Dr.Nishchol Mishra**



**Dr. Nishchol Mishra** is an Associate Professor at the School of Information Technology, Rajiv Gandhi Proudyogiki Vishwavidyalaya (RGPV), Bhopal. He joined RGPV as an Assistant Professor in 2007 and earned his PhD in 2014, specializing in Multimedia Data Mining.

He has guided 50 MTech students, with 1 PhD awarded, 2 submitted, and 4 ongoing. Dr. Nishchol Mishra has over 60 publications in international journals and contributions to more than 15 conferences, with research interests spanning Data Analytics, Image Mining, Big Data, Cybersecurity, and Digital Forensics.

He has presented research at IEEE in Athens, Greece, and was a topper in the NPTEL course titled "Towards an Ethical Digital Society: From Theory to Practice." He also ranked in the top 5% in the NPTEL course on Intellectual Property at the All India level.

Dr. Nishchol Mishra has conducted over 20 training programs and imparted training to gazette officers at the Sashastra Seema Bal Academy, Bhopal. Additionally, he has completed projects under Madhya Pradesh Council of Science and Technology (MPCST) and Ministry of Electronics and Information Technology (MeitY).

He is a member of prestigious bodies like CSI and ISTE, and serves as the Co-Chief Investigator for the ISEA Project Phase II, a national Information Security initiative by the Ministry of Electronics and IT, India. He holds multiple certifications, including EMCISA, EMCCIS, and a Postgraduate Diploma in Cyber Law from NLIU, Bhopal.

## Brief Bio of Mr. Pankaj Pandey



**Mr. Pankaj Pandey** is the Assistant Professor and Head of the Computer Science and Engineering Department at Jai Narain College of Technology (LNCT Group) in Bhopal. With over 11 years of experience in teaching and administration, he is currently pursuing his PhD in Computer Science and Engineering at Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal.

He holds both M.Tech and B.Tech degrees in Computer Science and Engineering. Mr. Pandey's research focuses on cybersecurity, data science, artificial intelligence, and machine learning. He has several patents for his innovations in autonomous driving and touch detection technologies.

As President of the Ministry of Education's Institute Innovation Cell at JNCT Bhopal, he has successfully organized impact lectures funded by the MoE and the MP Police Hackathon sponsored by Madhya Pradesh Police. Mr. Pandey has also mentored startups like InkThemes and TheKabaadiwala.com and has been involved in organizing academic and entrepreneurial activities, including workshops and industrial visits.

Certified in data science and cybersecurity, he has published numerous research papers and presented at conferences. His aim is to leverage his expertise to enhance his institution and advance the fields of technology and education.

## Brief Bio of Mr. Aditya Mandloi



Aditya Mandloi is a student of science stream in the final year of high school (standard XII) at the Sanskaar Valley School in Bhopal, holding the position of deputy head boy in school council. He has keen interest in STEM subjects and his commitment towards mitigating climate change set him on path of approaching the prestigious technical university in Bhopal to look for solutions of reducing pollution using artificial intelligence, machine learning and other modern scientific tools through Sarani thermal power plant for action research project.

Aditya is an accomplished public speaker, recognized for his impactful presentations at TEDx and MU20x (Asia's Biggest High School Leadership Conference). His two talks, available on YouTube, continue to inspire viewers around the globe.

His theatrical talents has taken him to the center stage in some of the nation's most prestigious venues—NCPA, Siri Fort, and others—portraying the lead role of Dr. APJ Abdul Kalam in the acclaimed play *Parwaaz Ka Aghaaz*, written by Gulzaar Sahib, one of greatest Urdu poets of this era.

Aditya has showcased his athletic prowess as an All-India Tennis rank holder. He has earned numerous victories and accolades in Lawn Tennis, having competed in 16 national tournaments and achieving a state ranking of 14.

He is the founder of Jaagruk, a free mobile application that simplifies access to government welfare schemes supporting and understanding the unorganised labour sector in Madhya Pradesh.

Aditya aspires to pursue a career in engineering as it offers diverse opportunities to solve real-world problems using creativity, science, and technology. He feels that It's a dynamic profession with endless possibilities for growth, making a lasting impact on society.



# Appendix

## Algorithm 1: Predict Emissions With Prophet

### Step 1: Import Libraries

- ⇒ Import Prophet from prophet.
- ⇒ Import pandas as pd.
- ⇒ Import numpy as np.
- ⇒ Import sklearn for hyperparameter tuning.

### Step 2: Load and Prepare Data

- ⇒ Load emission data into the dataframe `df`.
- ⇒ Ensure `df` has columns 'ds' (date) and 'y' (emission values).

### Step 3: Specify Holidays

- ⇒ Define a holidays dataframe `holidays_df` with columns 'ds' (date) and 'holiday'.
- ⇒ Add national holidays and maintenance periods to `holidays_df`.

### Step 4: Define and Configure Prophet Model

- ⇒ Initialize the model as `Prophet(holidays=holidays_df)`.

### Step 5: Hyperparameter Tuning

- ⇒ Define `param_grid` with ranges for `changepoint_prior_scale`, `seasonality_prior_scale`, and `holidays_prior_scale`.
- ⇒ Initialize `best_params` as an empty dictionary.
- ⇒ Initialize `best_score` as positive infinity.
- ⇒ For each combination of parameters in `param_grid` do:
  - a. Set model parameters.
  - b. Split `df` into `train_df` and `val_df`.
  - c. Fit the model with `train_df`.
  - d. Predict on `val_df`.
  - e. Calculate the performance metric (e.g., MAE or RMSE).
  - f. If the current score is better than `best_score` then:
    - g. Update `best_params` and `best_score`.
    - h. End if.
  - i. End for.

## Algorithm 2: ARIMA Time Series Forecasting

### Step 1. Import Libraries:

- ⇒ import statsmodels.api as sm
- ⇒ import pandas as pd
- ⇒ import numpy as np
- ⇒ import matplotlib.pyplot as plt
- ⇒ import statsmodels.graphics.tsaplots as tsaplots

### Step 2. Load and Prepare Data:

Load time series data into dataframe `df`.

- ⇒ Ensure `df` has a datetime index and one column for values.

### Step 3. Identify Parameters:

- ⇒ Plot ACF and PACF to determine  $p$ ,  $d$ ,  $q$ .
- ⇒ Plot ACF: `tsaplots.plot_acf(df)`
- ⇒ Plot PACF: `tsaplots.plot_pacf(df)`
- ⇒ Determine  $p$  from significant lags in the PACF plot.
- ⇒ Determine  $q$  from significant lags in the ACF plot.
- ⇒ Determine  $d$  based on stationarity tests (e.g., ADF test).

### Step 4. Fit the ARIMA Model:

- ⇒ Define the model as `sm.tsa.ARIMA(df, order=(p, d, q))`.
- ⇒ Fit the model: `model.fit()`.

### Step 5. Make Forecasts:

- ⇒ Define `forecast_steps` (number of periods to forecast).
- ⇒ Generate forecast: `model.forecast(steps=forecast_steps)`.
- ⇒ Calculate performance metrics (e.g., MAE, RMSE)

### Step 6. Output Results:

- ⇒ Print or plot the forecast results.
- ⇒ Return model, forecast, and performance metrics.