

# Idea Proposal

## Air Quality Trends and Thermal Power Correlation in Korea (2003–2024)

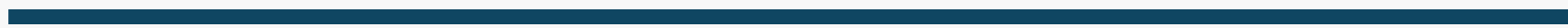
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# Basic Idea

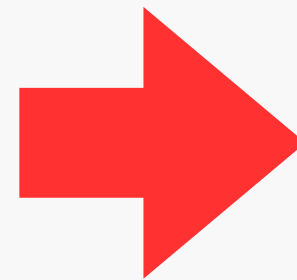
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## Problem

Sustained air quality degradation since 2003, driven by economic growth and increased energy demand.

**Hypothesis:**  
The rise in national thermal power generation has negatively impacted air quality.



## Goal

- Quantitatively analyze long-term trends linking energy demand and air quality.
- Systematically explore the correlation between thermal power output and pollutant concentration.

Establishment of a “**Self-updating Analytical Pipeline**” by automating data collection, loading, and analysis on a monthly basis.

# System overview and architecture

## Flow



# System overview and architecture

## Why automated collection?



**Data Source**



- **Regular Data Updates** - Automation ensures new data is collected on schedule without manual effort.
- **Consistency & Accuracy** - Uses the same extraction process every time → prevents human error. Guarantees consistent file format.
- **Efficiency** - Saves time by removing repetitive manual downloads.
- **Reliability** - System runs even without human intervention.
- **Integrated Pipeline** - Automated flow: Web Crawling → Hadoop HDFS → Hive → Python Analysis

# System overview and architecture

- **Why Hadoop?**

- Designed to **handle multi-year, large-scale air quality data efficiently**
- Provides distributed storage and automatic replication **for reliability**
- Enables **parallel access and high throughput** for data processing
- Selected to **support scalable, fault-tolerant storage** within our ETL pipeline



**Storage &  
Management**



- **Why Hive?**

- Integrated smoothly with Spark and HDFS** for batch data processing
- Enabled Parquet conversion and partitioning to optimize query speed
- Supported automated **ETL scheduling** for a self-updating pipeline
- Chosen over Impala as it **fits monthly batch analysis** better than real-time querying

# System overview and architecture

## Why Spark?



Processing

- **Spark** is an essential distributed processing framework for handling **massive datasets** like 21 years of hourly data
  - Used to avoid the **slow speeds** and potential **memory errors** (OOM) of single-server Python environments
  - Performs complex aggregation operations like groupBy and avg **dozens of times faster** by distributing data across multiple nodes
- **Pre-processes the air quality data into monthly averages efficiently!**

# System overview and architecture

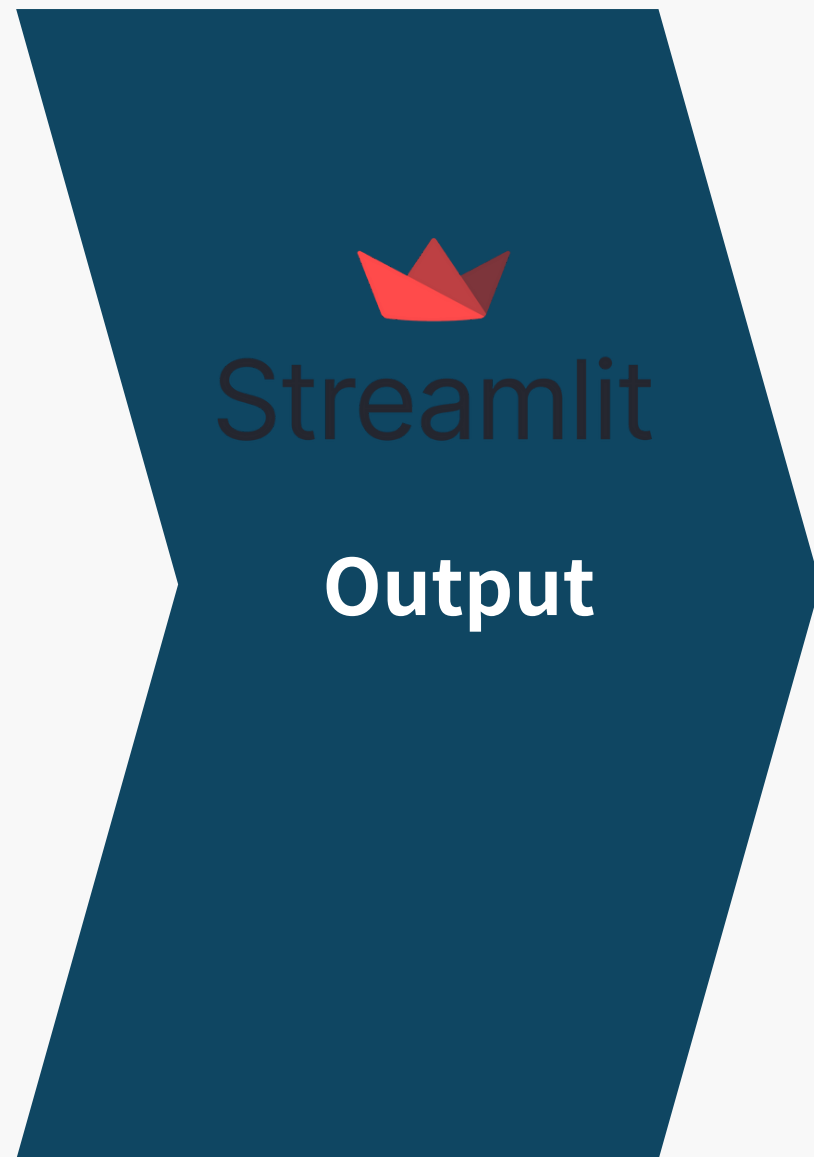
## Why Python?



- To perform flexible data analysis, correlation, and visualization.
- To perform flexible data analysis, correlation, and visualization.
- We import Spark's results (CSV or Parquet) into Python to compute correlation coefficients like Pearson and Spearman, and to visualize results with heatmaps and line charts.
- In short, Python is ideal for **in-depth statistical analysis and visualization after distributed processing.**



# System overview and architecture



## Why Streamlit?

- We wanted to make our analysis results easy to explore and share on the web.
- So, we built an **interactive dashboard** instead of using static charts.
- Streamlit, a **Python-based framework**, lets us create such dashboards quickly without any HTML or CSS, **supporting real-time visualization** and data filtering.

# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ① Data Source Layer

- Data Composition

No.	Source	Main Attributes	Period	Format	Purpose
①	Air Quality Data (AirKorea, Ministry of Environment)	Region, Station Code, Timestamp, SO <sub>2</sub> , NO <sub>2</sub> , O <sub>3</sub> , CO, PM10, PM 2.5, Address	2003–2024	CSV (monthly files)	Analyze hourly air pollution trends nationwide
②	Power Generation Data (KEPCO)	Year, Region, Power Generation (MWh)	2003–2024	CSV (annual statistics)	Examine thermal power generation and electricity usage patterns

# System overview and architecture

## Flow:

Data Source → Storage & Management → Processing → Analysis → Output

### ① Data Source Layer

#### Automated Data Collection:

- Collect monthly finalized air quality and power generation data using Linux cron scheduler and Python BeautifulSoup (web crawling).
- Automatically executed on the 1st day of each month to retrieve data from the previous month.



	A	B	C	D	E	F	G	H	I	J	K
1	지역	측정소명	측정소코드	측정일시	SO2	CO	O3	NO2	PM10	주소	
2	서울	중구	111121	2013010101	0.006	1.1	0.003	0.061	30	서울 중구 서소문동	
3	서울	중구	111121	2013010102	0.006	1.1	0.003	0.058	42	서울 중구 서소문동	
4	서울	중구	111121	2013010103	0.006	0.9	0.003	0.051	46	서울 중구 서소문동	
5	서울	중구	111121	2013010104	0.006	0.9	0.004	0.046	30	서울 중구 서소문동	
6	서울	중구	111121	2013010105	0.005	0.8	0.005	0.039	25	서울 중구 서소문동	
7	서울	중구	111121	2013010106	0.005	0.9	0.004	0.041	34	서울 중구 서소문동	

구 월별	기 력					계 Total
	무 연 탄 Anthracite coal	유 연 탄 Bituminous coal	중 유 Heavy oil	Steam L N G		
1	258,157	14,317,161	-	20,781		14,596,098
2	138,412	11,818,512	-	13,200		11,970,123
3	117,616	10,026,705	-	33,043		10,177,364
4	122,285	9,404,183	-	13,670		9,540,138
5	183,507	8,869,192	-	26,641		9,079,339
6	195,036	10,789,182	-	85,411		11,069,629
7	178,624	14,185,887	-	85,437		14,449,949
8	240,716	15,918,481	-	161,128		16,320,325
9	196,978	12,441,738	-	68,539		12,707,255
10	25,838	9,676,802	-	64,663		9,767,303
11	123,402	9,574,087	-	11,940		9,709,429
12	210,182	11,792,530	-	1,973		12,004,685

# System overview and architecture

## Flow:

**Data Source** → Storage & Management → Processing → Analysis → Output

## Web Crawling:

### Implementation

- Developed a Python-based web crawler using the requests library.
- The script sends a GET request to the official AirKorea endpoint.
- Downloads daily measurement data as an Excel file (.xls) for each monitoring station.

### Automation

- Scheduled via Linux cron job.
- Runs automatically on the 1st day of each month.
- Retrieves the previous month's data without manual intervention.

# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ② Data Storage & Management Layer

### Hadoop HDFS



- **Path:** /user/airquality/year=YYYY/month=MM/
- **Function:** Stores daily air quality data in raw CSV format before preprocessing.
- **Feature:** Splits files into blocks and distributes them across multiple DataNodes for parallel processing and reliability.

### Hive (Data Warehouse)

- **Role:** Enables SQL-like querying on data stored in HDFS / CSV → Parquet conversion
- **Table Structure:**
  - **External table:** air\_quality (raw)
  - **Partitions:** year, month
  - **Main columns:** region, timestamp, so2, no2, pm10, pm25, etc.



# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ③ Data Processing Layer



### Spark

- Calculate the monthly average for 21 years of national hourly air quality data

#### 1) Data Preprocessing & Loading:

- Load hourly CSV files from HDFS into Spark and normalize column names (KR→EN).
- Cast data types and fill missing values with mean.
- Save cleaned data as Parquet and register in Hive.

#### 2) Time Attribute Extraction:

- Extract Year and Month from the timestamp column to use as keys for correlation analysis.



# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ③ Data Processing Layer



### Spark

- Calculate the monthly average for 21 years of national hourly air quality data

#### 3) Monthly Aggregation:

- Perform groupBy(year, month) and apply avg() for each pollutant to calculate monthly national averages, aligning the time scale to enable equivalent comparison with power statistics.

#### 4) Data Extraction:

- Export the aggregated results as CSV files for subsequent Python-based correlation and visualization.

# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ④ Data Analysis & Visualization Layer

### Python (pandas, scipy, seaborn)

- Merge Spark output and power generation data into a unified dataset.
- Perform correlation (Pearson, Spearman), trend, and seasonality analyses to detect time-series patterns.
- Visualize results with heatmaps and line charts.



### Streamlit (Output visualization)

- Develop an interactive web dashboard to dynamically visualize analysis results.
- Enable users to explore timely trends, correlations, and download filtered data in real time.



Streamlit



# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ⑤ Output Layer

### 1. Correlation Results

- **Thermal Power Generation ↔ Air Quality Indicators (PM10, NO<sub>2</sub>, SO<sub>2</sub>):**

Calculate correlation coefficients to examine how power generation intensity affects air pollution levels.

- **Temporal Correlation Changes:**

Visualize how the relationship between power generation and air pollutants evolves over time (2003–2024).

# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## ⑤ Output Layer

### 2.Trend Visualization

- **Time-Series Trends:**

Display nationwide trends in PM 10 and NO<sub>2</sub> concentrations over 21 years.

- **Monthly Generation vs. Pollution Curves:**

Plot comparative graphs showing monthly generation output and pollutant fluctuations.

- **Automated Monitoring Insight:**

Demonstrate the potential of a self-updating analytical pipeline that continuously collects, processes, and visualizes data for real-time environmental monitoring.

# System overview and architecture

Flow:

Data Source → Storage & Management → Processing → Analysis → Output

## Extract

**Data Source 1:**  
Air Quality Data  
(AirKorea)

**Data Source 2:**  
Power Generation Data  
(KEPCO)

## Transform

**Transformation Engine:**  
Apache Spark

**Transformation Logic:**

- ① Aggregate of air quality data
- ② Prepare for combining with power generation data

## Load

**Target:**  
Python & Streamlit



# System overview and architecture

## Cluster Configuration: 3 Node Cluster

### One Master Node:

- NameNode in HDFS
- Cluster Resource Management
- DB Schema Management (Hive Metastore)
- Spark Task Distribution

### Two DataNodes:

- Storage of Data Blocks
- Spark Job Execution

### One Client:

- Automated Data Collection
- Python-based Analysis

- **Implementation: Docker based VM:**

Each node runs independently in a separate container within the same Docker network, enabling efficient inter-node communication and easy scalability.

# Intermediate results

데이터베이스



air\_quality\_db

테이블 이름...

air\_quality



- ☐ region (string)
- ☐ station\_name (string)
- ☐ station\_code (string)
- ☐ timestamp\_raw (string)
- ☐ so2 (float)
- ☐ co (float)
- ☐ o3 (float)
- ☐ no2 (float)
- ☐ pm10 (int)
- ☐ pm25 (int)
- ☐ address (string)
- ☐ year (int)
- ☐ month (int)

열

파티션 열

샘플

속성



0

1



year

month

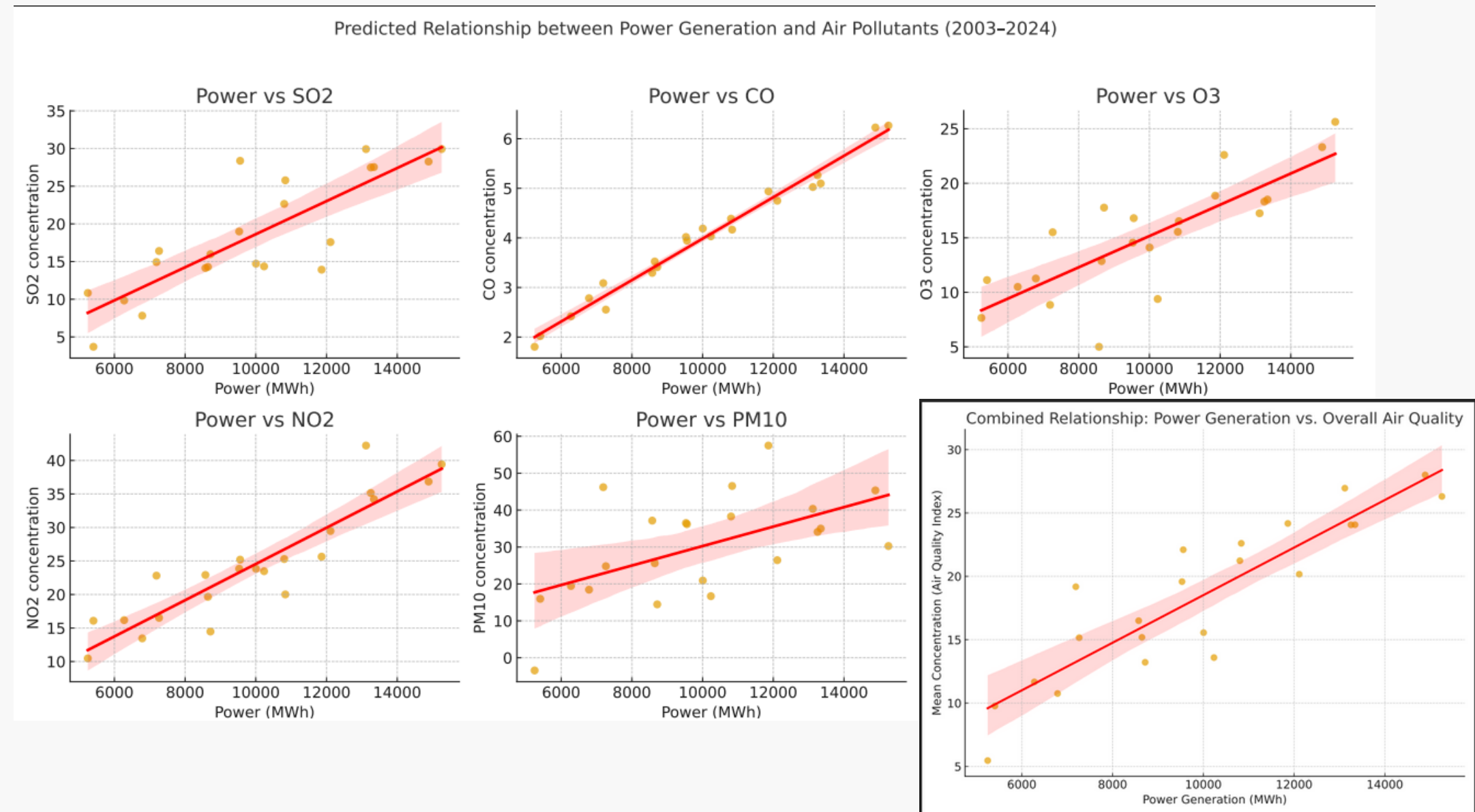
데이터베이스 > air\_quality\_db > air\_quality

열 파티션 열 샘플 속성

	region	station_name	station_code	timestamp_raw	so2	co	o3	no2	pm10	pm25	address	year	
0	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.5	0.0419999994338	0	36	26	2022	5
1	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.5	0.0399999991059	0	27	22	2022	5
2	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.400000000596	0.0370000004768	0	25	17	2022	5
3	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.400000000596	0.0370000004768	0	27	14	2022	5
4	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.400000000596	0.0320000015199	0	25	15	2022	5
5	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.5	0.02600000005364	0	25	14	2022	5
6	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.5	0.0179999992251	0	24	16	2022	5
7	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.400000000596	0.0289999991655	0	25	14	2022	5
8	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.400000000596	0.0340000018477	0	29	8	2022	5
9	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.400000000596	0.035000000149	0	35	8	2022	5
10	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.300000011921	0.0410000011325	0	37	14	2022	5
11	서울 중구	도시대기	111121	중구	2022050048.0	0.00300000002608	0.300000011921	0.0469999983907	0	49	10	2022	5
12	서울 중구	도시대기	111121	중구	2022050176.0	0.00300000002608	0.300000011921	0.0509999990463	0	51	9	2022	5
13	서울 중구	도시대기	111121	중구	2022050176.0	0.00300000002608	0.300000011921	0.0529999993742	0	40	6	2022	5
14	서울 중구	도시대기	111121	중구	2022050176.0	0.00300000002608	0.300000011921	0.0610000006855	0	30	6	2022	5
15	서울 중구	도시대기	111121	중구	2022050176.0	0.00300000002608	0.300000011921	0.0630000010133	0	27	11	2022	5
16	서울 중구	도시대기	111121	중구	2022050176.0	0.00400000018999	0.300000011921	0.0640000030398	0	28	15	2022	5
17	서울 중구	도시대기	111121	중구	2022050176.0	0.00400000018999	0.300000011921	0.0619999989867	0	28	13	2022	5

# Expected results

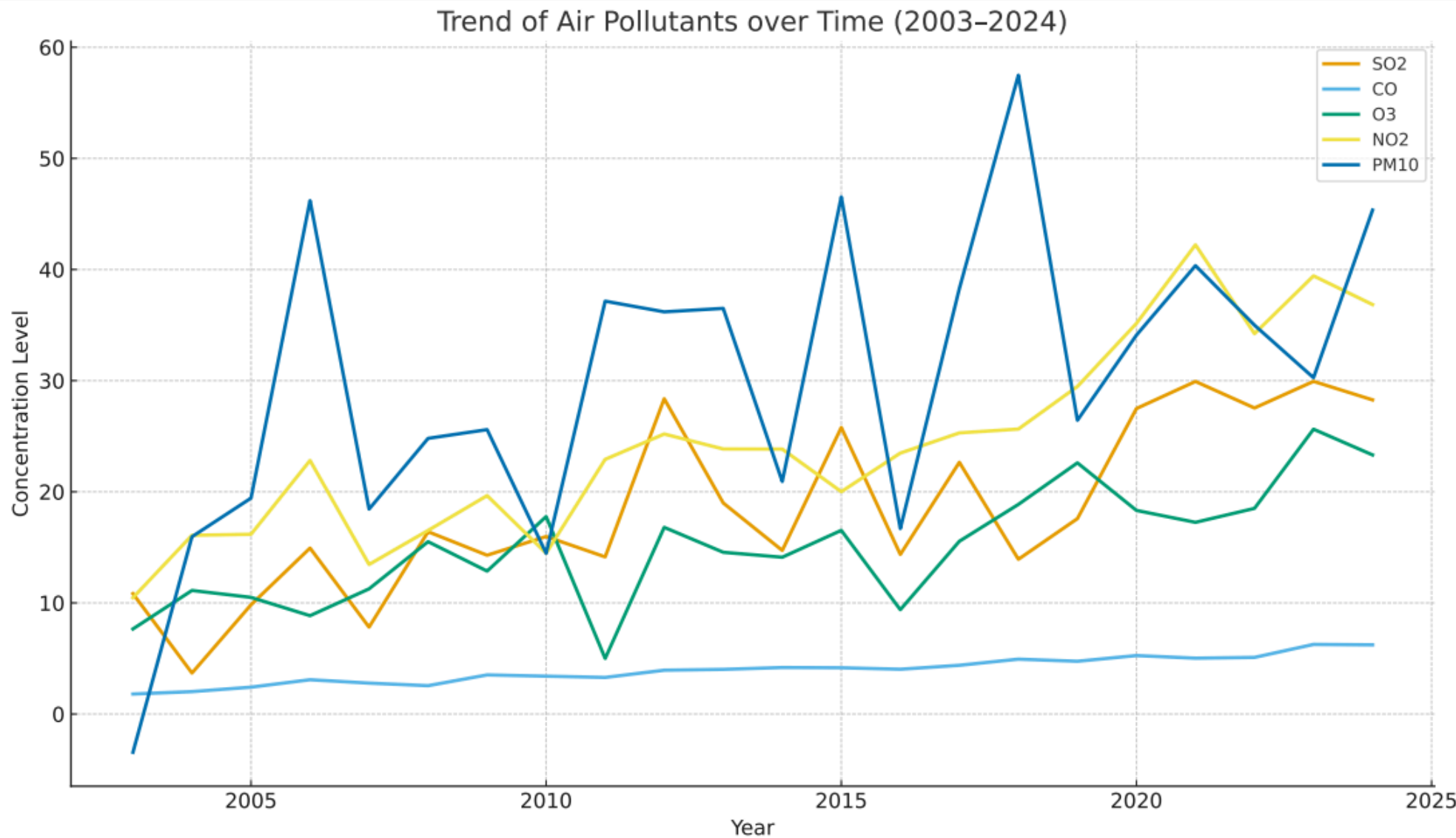
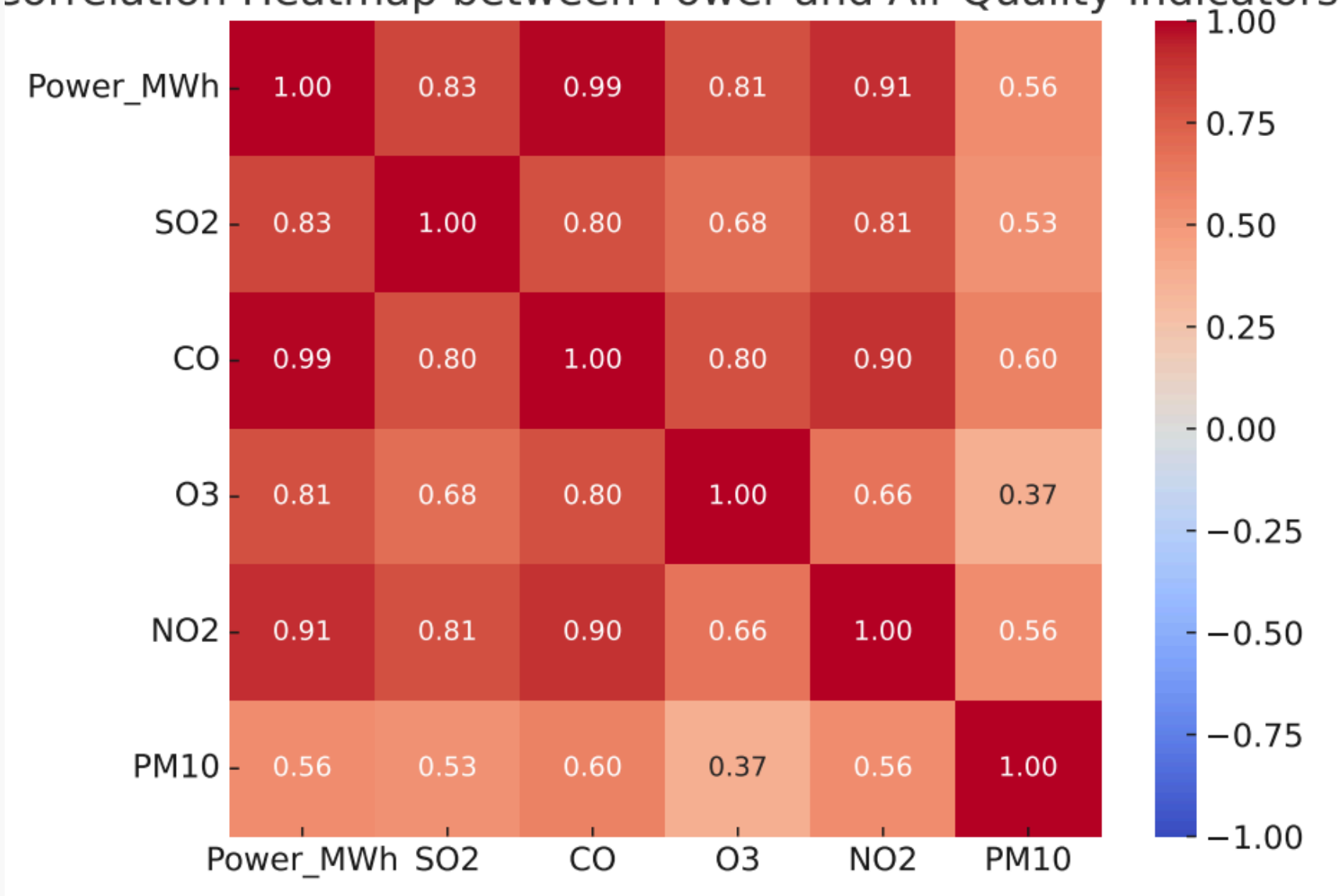
- Increased thermal power generation shows strong positive correlations with SO<sub>2</sub>, CO, NO<sub>2</sub>, and PM10.
- Seasonal patterns indicate higher pollutant levels during high energy-demand periods.
- Results support the hypothesis that rising power output has negatively impacted air quality.





# Expected results

Correlation Heatmap between Power and Air Quality Indicators







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**Thank you**

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