

Markov chain modeling of Air Quality Index transitions in Mumbai metropolitan region during 2024 – 2025

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Abstract

Air pollution always remains as the major environmental and public health threat, rapidly increasing in many urban areas. The accurate management of Air Quality Index (AQI) is essential for effective environmental protection and policy intervention. This study applied discrete time Markov chain model to investigate the transition behaviour of AQI state based on health standards like Good, Satisfactory, Moderate, and Poor across different monitoring stations in the Mumbai Metropolitan Region (MMR) during 2024 – 2025. The transition probabilities were used to understand the persistence, deterioration and recovery patterns of air quality. The study reported that the steady state analysis indicated that Moderate air quality remains persistent in long run condition across monitoring stations. The mean recurrence time indicated that expected number of days required for an AQI category to revisit after leaving that state. It was observed that on an average, the mean return time of Good state was decreased from 2024 to 2025, suggesting favourable air quality recurring more frequently in 2025. However, the comparison between 2024 and 2025 reveals slight improvement in air quality during 2025, characterized by reduced persistence rate of the poor category, longer mean recurrence rate for poor state of pollution and decreased mean transitions from Good to Poor states. Overall, the Markov Chain analysis highlighted a slight improvement in air quality from 2024 to 2025 across the MMR. The results demonstrated that Markov Chain modeling provides valuable insights in developing study specific threshold ranges, offering a statistically robust decision support framework for early intervention strategies and timely implementation of the Graded Response Action Plan (GRAP). Such proposed threshold ranges of AQI can support the achievement of Sustainable Development Goals (SDGs), particularly those related to sustainable urban planning, by concentrating on reduced vehicular emissions and improving overall air quality.

Keywords: *AQI; Air Quality; Markov Chain; Mumbai Metropolitan Region; SDGs*

Introduction

Air pollution has emerged as a major global environmental and public health concerns due to its adverse effects on human health. When the human body is exposed to high concentrations of air pollutants for longer periods, it can result in various health complications, like respiratory disorders, cardiovascular diseases and chronic lung conditions (Holmes and Hassini, 2021). The Air Quality Index (AQI), serves as a quantitative descriptor of air quality (Szyszkowicz,

2019), which can effectively depict the present level of air pollution as per the Central Pollution Control Board guidelines (Shah and Patel, 2021). Hence, accurate prediction of AQI enables early warning and reliable forecasting of air pollution episodes, thereby helping governmental and regulatory bodies to implement proactive strategies in order to mitigate air pollution and effective environmental management (Liu et al., 2024). There are many well-known forecasting model to solve real world problems such as

the Autoregressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Artificial Neural Network (ANN), Fuzzy Time series, ANN-Support Vector Machine (SVM) and regression modelling (Masoudi et al., 2018) was widely used to understand the seasonal patterns and temporal trends in pollutant concentrations (Elgharbi et al., 2020; Masoudi et al., 2019). Many Machine Learning models are widely used in predicting AQI values, but they often concentrate on forecasting values of AQI and may not explicitly describe the probabilistic transitions between different states of pollution. The Markov chain model was introduced in the beginning of 20th century and widely implemented in many streams like geography, meteorology, biology, physics, behavioural, social sciences and many more (Mohamad et al., 2018). The discrete time Markov Chain is a probabilistic model used to analyse stochastic processes. Such models are widely used in modelling precipitation, infrastructure deterioration and wind modeling (Sahin and Sen, 2001; Holmes and Hassini, 2021). The Markov process was also employed in daily rainfall analysis in order to understand the dry, wet and rainy conditions among the states of Brazil (Jale et al., 2019). Researchers also used Markov chain model for modeling for weather data (Shinde & Chavhan, 2018). Many studies also used Markov chain to model air pollution (Caraka et al., 2019). The study (Nebenzal and Fishbain, 2018) also reported that in order to forecast long term NO₂ pollution, Markov chain models minimizes the error as compared to other forecasting models. The Markov model emphasizes on uncertainty quantification and transition behaviour rather than focusing on predicting values for pollutant concentration. With regards to environmental management and to achieve sustainable development goals (SDG Indicator 3.9.1), understanding the chance of moving from one pollution category to another is often useful. Specifically, this approach supports SDG 11 (Sustainable Cities and Communities) by enabling better urban air quality management, and SDG 3 (Good Health and Well Being) by addressing risk associated with longer exposure to poor air quality conditions. For policymakers, knowing the chance that air quality deteriorate from Good to Poor within a short period is often more actionable than single predicted values of AQI. This shift of focusing on transition based risk assessment also contributes to SDG 13 (Climate Action) by facilitating proactive and adaptive measures in response to changing environmental conditions. Most of the air pollution studies

used Markov modelling which focused on specific concentrations of pollutants like Particulate matter (Mohamad et al., 2018), Ozone and Sulphur Dioxide (Rodrigues et al., 2019), while very few studies concentrates on using Markov chain modelling for AQI categories across multiple monitoring stations (Holmes and Hassini, 2021; Zakaria et al., 2019). The Markov framework on AQI categories simplifies complex environmental dynamics into structured transition process. Such models are highly relevant for urban governance, especially in metropolitan regions where the air quality levels fluctuates frequently due to anthropogenic and meteorological factors. Therefore, the present study aims to bridge this gap by applying a discrete-time Markov chain model to examine transitions of AQI across monitoring stations in Mumbai Metropolitan Regions (MMR) during 2024 –2025. A discrete time Markov chain by assuming homogeneous transitions was fitted for AQI categories in order to obtain the following objectives:

- (i) to model the temporal transition of AQI categories using a discrete time Markov chain process;
- (ii) to estimate steady state probabilities in order to assess the pollution persistence and mean recovery patterns;
- (iii) to estimate Mean First Passage time of AQI category transitions in selected air quality monitoring stations;
- (iv) to suggest recommendations for sustainable urban environmental management.

Materials and methods

Study Area

The Mumbai Metropolitan region (MMR) is one among the largest metropolitan region in the world, approximately 22.8 million population and covered an area of 4254 sq.km. The region consists of urban, suburbs, industrial and peri-urban zones, leads to notable variations in air quality levels (Final Regional Plan for Mumbai Metropolitan Region Report English, 2021) (Fig. 1). There are 44 air quality monitoring stations within MMR, operated by Maharashtra Pollution Control Board (MPCB), the Indian Institute of Tropical Meteorology (IITM), and the Brihanmumbai Municipal Corporation (BMC). These stations provides data on continuous measurements of major air pollutants which is useful for regulatory monitoring and public health assessment.

Data processing

This study used the available data for each monitoring

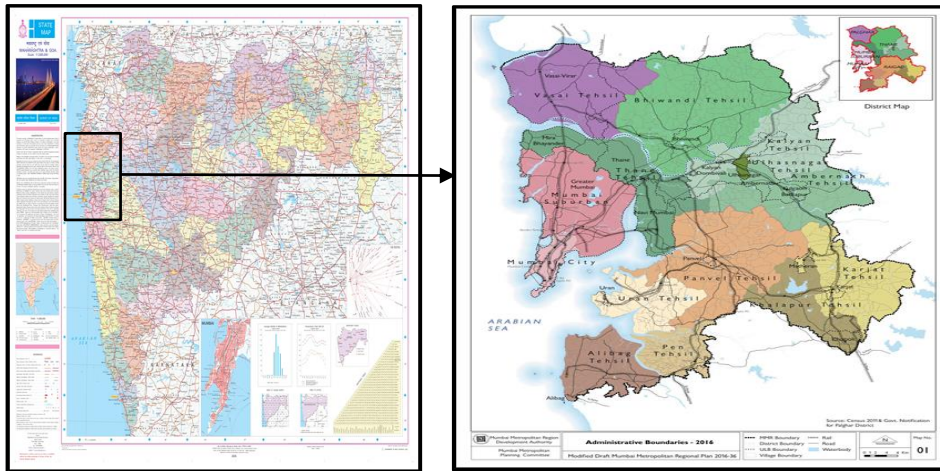


Figure 1
Map of study area

station from Central Pollution Control Board (CPCB) for air pollutants like $PM_{2.5}$, PM_{10} , NO_2 , SO_2 , NH_3 , Pb, Nitrogen Oxides (NO and NO_x) on a 24-hour basis, but CO and O_3 , were retrieved on 8-hour basis from 1st January 2024 to 31st December 2025. The total number of observations in the dataset for 44 monitoring stations in the year 2024 was 15,354 station-days, while for 2025 it was 15,208 station-days. The overall data coverage for 2024 and 2025 was 95.34% and 94.69%, respectively, indicating the presence of missing observations in both years. Since the Markov Chain modeling requires a continuous dependency across consecutive days, all 44 stations were initially examined. To ensure reliability of data, monitoring stations with more than 25 missing observations were excluded from further analysis. After this filtering, 37 stations were employed for 2024 and 33 stations for 2025, with 13,542 and 12,045 stations days respectively used for further analysis. The missing values for 37 stations in 2024 and 33 stations in 2025 were estimated using Markovian simulation techniques implemented in R Software. The missing days were imputed based on the transition probabilities between air quality states, ensuring that the simulated values do not alter the temporal pattern of air quality. All Markov chain analysis in the given study were performed using R software, assuming a homogenous Markov chain in the given time period. This assumption helps to better understand the long term behaviour of air quality.

Classification of AQI

The AQI is a simple and effective tool used to understand the quality of air which inculcate pollutants like Particulate matter of size 2.5 ($PM_{2.5}$), Particulate matter of size 10 (PM_{10}), Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), Carbon Monoxide (CO), Ozone (O_3), and Ammonia (NH_3) into a single measure that reflects overall air pollution levels and associated

health risks. The AQI serves as a decision making tool for policymakers, urban planners and public health authorities. To apply Markov chain modeling, the AQI using CPCB based health breakpoints was classified into four categories like Good, Satisfactory, Moderate and Poor as represented in Table 1.

AQI range	AQI Category
0 – 50	Good
51 – 100	Satisfactory
101 – 200	Moderate
201 and above	Poor

Table 1
Classification of
Air Quality Index

Discrete-time Markov chain model

We defined a discrete-time stochastic process as $\{X_t, t = 0, 1, 2, \dots\}$, where t denotes time measured in days. The random variable X_t denotes the AQI category observed on day t (Sheldon Ross, 1995). The process takes values in a finite state space defined as $S = \{0, 1, 2, 3\}$, corresponding to Good (0), Satisfactory (1), Moderate (2) and Poor (3) air quality states.

For each monitoring station,

$$X_t = \begin{cases} 0, & \text{if AQI on day } t \text{ is in Good State} \\ 1, & \text{if AQI on day } t \text{ is in Satisfactory State} \\ 2, & \text{if AQI on day } t \text{ is in Moderate State} \\ 3, & \text{if AQI on day } t \text{ is in Poor State} \end{cases}$$

The Markov property assumes that the probability distribution of AQI state on day $t+1$ depends only on its state on day t , and is conditionally independent of previous states which defined as follows (Medhi, 2012)

$$P\{X_{t+1} = j | X_t = i, X_{t-1} = i_{t-1}, X_0 = i_0\} = P\{X_{t+1} = j | X_t = i\} = p_{ij}$$

for all states $i, j, i_0, \dots, i_{t-1} \in S, t = 0, 1, \dots$

where, transition matrix $P = [p_{ij}]$ represents non-negative elements with row sum unity.

$$\text{i.e. } 0 \leq p_{ij} \leq 1 \text{ and } \sum_j p_{ij} = 1 \text{ for all } i, j \in S \quad [1]$$

With respect to AQI dynamics, this depicts that tomorrow's AQI category will depend on today's pollution condition, assuming that present state sufficiently summarizes the influence of past meteorological and emission factors.

Model assumptions

Test for Markov dependence. In order to check the basic assumption of Markov model, Chi square test of independence was used to understand if present state of AQI depends on past state of AQI as defined equation [2]. The null hypothesis states that the selected transition of AQI on consecutive days (t) is independent while the alternative hypothesis is the selected transition of AQI on consecutive days (t) is dependent. The null hypothesis is rejected when $\chi_{calculated}$ is greater than $\chi_{tabulated}$ on 5% level of significance (p value < 0.05) (Holmes and Hassini, 2021).

$$\text{where, } \chi_{calculated}^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}} \quad [2]$$

Once the null hypothesis is rejected, it indicates the temporal dependence in AQI transitions, validating the Markov modeling framework.

Determination of Markov order. In order to determine the appropriate dependence structure, the Markov chain models for order 0 and 1 were fitted for each monitoring station.

Order 0 indicates that the future state X_{t+1} is independent of past states ($X_t, X_{t-1}, \dots, X_0$).

Order 1 indicates future state X_{t+1} depends only on the present state X_t .

Model selection was done using the Akaike Information Criterion (AIC) based on Minimum Akaike Information Criterion Estimation (MAICE) (Medhi, 2012).

$$AIC(k) = -2\ln(L_k) + 2p_k \quad [3]$$

where, k = Order of the Markov Chain; $\ln(L_k)$ = Maximized log-likelihood of k-th order chain; p_k = Number of independent parameters in the model.

For each monitoring station, the Markov chain order with the smallest AIC was selected as represented in Table 2. Markov chain of the first order process was observed throughout the monitoring station in order to ensure uniform modelling and interpretability across monitoring stations over the study period.

Confirmation of Ergodic Markov chain. For a long run analysis, the confirmation of Ergodic Markov chain must be made in order to determine the existence of

limiting stationary distribution by evaluating three key properties: irreducibility, aperiodicity and recurrence (Zakaria et al., 2019). A Markov chain is said to be irreducible if every state can be accessible from every other state in finite number of transitions. In other words all states communicates with each other forming one communicating class (Zakaria et al., 2019). A Markov chain is said to be aperiodic, if return to a particular state do not occur in fixed repeating cycles (Zakaria et al., 2019). A state is said to be recurrent if the process guarantees to return back to the same state with probability one (Zakaria et al., 2019). Furthermore, the mean recurrence time for state j denoted as μ_{jj} (Medhi, 2012) is used to identify the expected number of days for specific states to return back to itself after leaving it can be obtained using equation [4]

$$\mu_{jj} = \sum_{n=1}^{\infty} n f_{jj}^{(n)} ; \text{ for all } j \in S, n = 1, 2, \dots \quad [4]$$

where $f_{jj}^{(n)}$ = probability that starting with state j the system will reach state j for the first time after n transitions.

Additionally, the Mean first passage time (Prasad and Namboodiri, 2020) from state i to state j, referred as μ_{ij} , is the expected number of steps taken by Markov Chain to arrive at state j, after starting from state i in first time can be obtained using equation [5].

$$\mu_{ij} = \sum_{n=1}^{\infty} n f_{ij}^{(n)} \text{ for all } i, j \in S, n = 1, 2, \dots \quad [5]$$

where $f_{ij}^{(n)}$ = probability that starting with state i the system will reach state j for the first time after n transitions (Medhi, 2012).

Results

Steady state probabilities

The steady state probabilities represented in Table 3 describes the long term behaviour of air quality at each monitoring station. These probabilities indicates the proportion of days that air quality is expected to remain in each AQI category over a long period, independent of initial condition. However, stations like BKC, Bolinj Virar, CBD Belapur, Kopripada Vashi, Mira Bhayandar and Upvan depicted a noticeable improvement in 2025, with increased chance of Good and satisfactory categories and reduced persistence of Poor air quality levels. Overall, the MMR is transitioning towards satisfactory level of air quality in 2025. However many stations consistently experiencing moderate level of air quality, suggesting ongoing pollution sources that continue to affect these areas.

Air Quality Monitoring Station	Year	AIC for		Selected Order
		Order-0	Order-1	
Bandra Kurla Complex, Mumbai (MPCB)	2024	791.99	670.62	1
	2025	813.77	705.83	1
Bolinj, Virar (MPCB)	2024	782.72	705.74	1
	2025	792.02	749.69	1
Borivali East, Mumbai (IITM)	2025	769.65	698.85	1
Borivali East, Mumbai (MPCB)	2024	732.04	665.77	1
Byculla, Mumbai (BMC)	2024	852.73	738.74	1
	2025	826.14	706.54	1
Colaba, Mumbai (MPCB)	2024*	767.17	716.84	1
	2025	756.71	752.49	1
CBD Belapur, Belapur (MPCB)	2024	760.49	663.69	1
	2025	869.17	701.14	1
Chhatrapati Shivaji Intl. Airport (T2), Mumbai (MPCB)	2024*	761.87	675.20	1
	2025*	547.80	403.47	1
Chakala Andheri East, Mumbai (IITM)	2024	838.56	744.38	1
	2025	787.06	727.24	1
Chembur, Mumbai (MPCB)	2024	908.48	757.96	1
	2025	836.44	718.53	1
Ghatkopar, Mumbai (BMC)	2024	853.81	718.85	1
	2025*	762.42	599.83	1
Gokul Nagar, Bhiwandi (MPCB)	2024	816.54	705.69	1
	2025	721.49	608.59	1
Kandivali East, Mumbai (MPCB)	2024	756.94	698.65	1
Kandivali West, Mumbai (BMC)	2024	880.95	784.90	1
	2025	723.99	613.66	1
Kasarvadavali, Thane (MPCB)	2024	863.00	733.75	1
	2025	751.65	683.33	1
Katrap, Badlapur (MPCB)	2024	855.71	777.95	1
	2025	695.99	581.98	1
Khadakpada, Kalyan (MPCB)	2024	766.60	638.91	1
Khindipada-Bhandup West, Mumbai (IITM)	2024*	789.91	676.57	1
	2025*	772.74	646.84	1
Kherwadi Bandra East, Mumbai (MPCB)	2024	859.00	705.04	1
	2025	843.76	712.65	1
Kopripada Vashi, Navi Mumbai (MPCB)	2024	899.01	790.56	1
	2025	810.01	717.80	1
Kurla, Mumbai (MPCB)	2024	784.63	742.85	1
	2025*	566.05	490.11	1
Mahape, Navi Mumbai (MPCB)	2024*	674.27	560.93	1
	2025*	733.65	614.84	1
Malad West, Mumbai (IITM)	2025	841.97	719.67	1
Mazgaon, Mumbai (IITM)	2024	929.07	827.08	1
	2025	798.85	726.56	1
Mindspace-Malad West, Mumbai (MPCB)	2024	828.73	715.31	1
	2025	816.07	683.82	1
Bhayandar West, Mira-Bhayandar (MPCB)	2024	899.83	745.36	1
	2025	809.88	697.30	1
Mulund West, Mumbai (MPCB)	2024	810.73	765.79	1
	2025	531.98	499.32	1
Navy Nagar-Colaba, Mumbai (IITM)	2024	843.02	796.52	1
	2025	814.41	683.84	1
Nerul, Navi Mumbai (MPCB)	2024	835.31	727.81	1
Powai, Mumbai (MPCB)	2024*	802.02	672.19	1
Sanpada, Navi Mumbai (MPCB)	2024	818.98	692.70	1
	2025	812.68	659.80	1
Sector 2E Kalamboli, Navi Mumbai (MPCB)	2024	839.45	765.65	1
	2025	805.55	701.82	1
Sewri, Mumbai (BMC)	2024	881.82	787.45	1
	2025	873.70	730.42	1
Shivaji Nagar, Mumbai (BMC)	2025	828.18	742.39	1
Siddharth Nagar-Worli, Mumbai (IITM)	2025	820.89	750.34	1
Siddhivinayak, Ulhasnagar (MPCB)	2024	770.33	666.03	1
	2025*	645.24	537.19	1
Sion, Mumbai (MPCB)	2024	775.35	696.31	1
Tondare Taloja, Navi Mumbai (MPCB)	2025	805.33	703.08	1
Upvan Fort, Thane (MPCB)	2024	893.55	740.71	1
	2025	800.45	737.42	1
Vasai West, Mumbai (MPCB)	2024	777.48	758.17	1
Vile Parle West, Mumbai (MPCB)	2024	798.37	776.62	1
Worli, Mumbai (MPCB)	2024	785.04	761.18	1

Table 2

Selection of Markov chain order (0/1).

Table 3. Steady state probabilities for each monitoring station.

Air Quality Monitoring Station	Steady state probabilities							
	Good		Satisfactory		Moderate		Poor	
	2024	2025	2024	2025	2024	2025	2024	2025
Bandra Kurla Complex, Mumbai (MPCB)	0.09	0.19	0.37	0.33	0.49	0.46	0.05	0.02
Bolinj, Virar (MPCB)	0.09	0.20	0.45	0.53	0.42	0.24	0.04	0.02
Borivali East, Mumbai (IITM)	NE	0.15	NE	0.50	NE	0.34	NE	0.01
Borivali East, Mumbai (MPCB)	0.47	NE	0.40	NE	0.13	NE	0.003	NE
Byculla, Mumbai (BMC)	0.42	0.40	0.31	0.29	0.24	0.30	0.03	0.01
Colaba, Mumbai (MPCB)	0.30	0.43	0.44	0.38	0.26	0.19	NR	0.01
CBD Belapur, Belapur (MPCB)	0.16	0.33	0.32	0.25	0.51	0.39	0.01	0.03
Chhatrapati Shivaji Intl. Airport (T2),Mumbai (MPCB)	0.18	0.05	0.41	0.70	0.41	0.25	NR	NR
Chakala Andheri East, Mumbai (IITM)	0.30	0.15	0.29	0.43	0.39	0.39	0.03	0.03
Chembur, Mumbai (MPCB)	0.31	0.28	0.29	0.32	0.35	0.38	0.05	0.01
Ghatkopar, Mumbai (BMC)	0.41	0.35	0.24	0.23	0.32	0.42	0.03	NR
Gokul Nagar, Bhiwandi (MPCB)	0.10	0.1	0.40	0.45	0.44	0.44	0.06	0.01
Kandivali East, Mumbai (MPCB)	0.24	NE	0.25	NE	0.51	NE	0.01	NE
Kandivali West, Mumbai (BMC)	0.43	0.51	0.27	0.38	0.22	0.09	0.08	0.01
Kasarvadavali, Thane (MPCB)	0.23	0.17	0.32	0.47	0.42	0.36	0.03	0.002
Katrap, Badlapur (MPCB)	0.12	0.09	0.30	0.47	0.50	0.45	0.08	0.002
Khadakpada, Kalyan (MPCB)	0.24	NE	0.23	NE	0.53	NE	0.01	NE
Khindipada-Bhandup West, Mumbai (IITM)	0.35	0.36	0.38	0.33	0.27	0.31	NR	NR
Kherwadi Bandra East, Mumbai (MPCB)	0.24	0.26	0.31	0.32	0.43	0.40	0.03	0.02
Kopripada Vashi, Navi Mumbai (MPCB)	0.19	0.25	0.22	0.38	0.49	0.37	0.10	0.01
Kurla, Mumbai (MPCB)	0.17	0.03	0.40	0.55	0.42	0.43	0.01	NR
Mahape, Navi Mumbai (MPCB)	0.14	0.15	0.26	0.35	0.60	0.50	NR	NR
Malad West, Mumbai (IITM)	NE	0.15	NE	0.43	NE	0.38	NE	0.04
Mazgaon, Mumbai (IITM)	0.22	0.15	0.27	0.46	0.41	0.34	0.09	0.04
Mindspace-Malad West, Mumbai (MPCB)	0.38	0.44	0.32	0.25	0.27	0.31	0.03	0.01
Bhayandar West, Mira-Bhayandar (MPCB)	0.25	0.37	0.25	0.30	0.44	0.32	0.06	0.01
Mulund West, Mumbai (MPCB)	0.24	0.01	0.40	0.63	0.36	0.34	0.01	0.02
Navy Nagar-Colaba, Mumbai (IITM)	0.10	0.11	0.42	0.46	0.39	0.38	0.09	0.05
Nerul, Navi Mumbai (MPCB)	0.19	NE	0.25	NE	0.52	NE	0.04	NE
Powai, Mumbai (MPCB)	0.29	NE	0.33	NE	0.38	NE	NR	NE
Sanpada, Navi Mumbai (MPCB)	0.17	0.24	0.35	0.19	0.46	0.53	0.03	0.04
Sector 2E Kalamboli, Navi Mumbai (MPCB)	0.17	0.19	0.29	0.40	0.50	0.41	0.04	0.01
Sewri, Mumbai (BMC)	0.30	0.23	0.36	0.34	0.30	0.36	0.05	0.07
Shivaji Nagar, Mumbai (BMC)	NE	0.16	NE	0.36	NE	0.42	NE	0.05
Siddharth Nagar-Worli, Mumbai (IITM)	NE	0.18	NE	0.45	NE	0.34	NE	0.04
Siddhivinayak, Ulhasnagar (MPCB)	0.04	0.06	0.41	0.49	0.47	0.45	0.07	NR
Sion, Mumbai (MPCB)	0.21	NE	0.29	NE	0.49	NE	0.01	NE
Tondare Taloja, Navi Mumbai (MPCB)	NE	0.20	NE	0.42	NE	0.37	NE	0.01
Upvan Fort, Thane (MPCB)	0.27	0.39	0.40	0.42	0.29	0.18	0.04	0.01
Vasai West, Mumbai (MPCB)	0.19	NE	0.41	NE	0.40	NE	0.003	NE
Vile Parle West, Mumbai (MPCB)	0.20	NE	0.40	NE	0.39	NE	0.01	NE
Worli, Mumbai (MPCB)	0.23	NE	0.43	NE	0.33	NE	0.003	NE

NE: Not Estimated due to insufficient data (>25 missing observations)
NR: Not revisited the state during the study period, SD: Standard Deviation

Mean return time of an AQI category

The Table 4 represents mean return time indicates the expected number of days required for a particular AQI category to return back to the same state after leaving it. The state that occurs more often has shorter return times while rare states exhibits longer return times. Across majority of the stations, the Satisfactory and Moderate categories demonstrated the shortest mean return times, generally ranging between 2 – 5 days which indicates that these air quality state recurred frequently throughout both years. On the other hand, the

good category depicted longer return time due to rare occurrence of Good category at stations like CSMT Airport (18 days) Kurla (33.30 days) and Mulund West (178.91). The Table 5 represents comparative analysis of air quality trends between 2024 and 2025 indicating improved air quality with good and satisfactory level of air quality occurring more frequently across many stations. in the year 2025. However, the moderate level of air pollution tends to persist for longer duration, while poor quality of air was less frequent.

Table 4. Mean return time of an AQI category for each monitoring station.

Air Quality Monitoring Station	Mean return time (in days)							
	Good		Satisfactory		Moderate		Poor	
	2024	2025	2024	2025	2024	2025	2024	2025
Bandra Kurla Complex, Mumbai (MPCB)	10.89	5.20	2.72	3.04	2.04	2.18	20.23	52.51
Bolinj, Virar (MPCB)	11.41	4.97	2.23	1.87	2.35	4.13	26.07	42.86
Borivali East, Mumbai (IITM)	NE	6.76	NE	1.98	NE	2.95	NE	121.75
Borivali East, Mumbai (MPCB)	2.13	NE	2.48	NE	7.90	NE	394.97	NE
Byculla, Mumbai (BMC)	2.38	2.47	3.25	3.47	4.11	3.37	34.97	94.36
Colaba, Mumbai (MPCB)	3.32	2.35	2.28	2.63	3.84	5.37	NR	106.49
CBD Belapur, Belapur (MPCB)	6.19	3.01	3.09	3.99	1.96	2.58	182.5	33.54
Chhatrapati Shivaji Intl. Airport (I2), Mumbai (MPCB)	5.41	18.54	2.45	1.44	2.46	3.99	NR	NR
Chakala Andheri East, Mumbai (IITM)	3.37	6.51	3.43	2.33	2.60	2.57	37.49	36.77
Chembur, Mumbai (MPCB)	3.25	3.53	3.41	3.09	2.84	2.62	21.51	89.63
Ghatkopar, Mumbai (BMC)	2.46	2.90	4.12	4.26	3.16	2.38	29.5	NR
Gokul Nagar, Bhiwandi (MPCB)	10.44	10	2.5	2.22	2.26	2.26	16.14	179.44
Kandivali East, Mumbai (MPCB)	4.23	NE	4.02	NE	1.96	NE	182.62	NE
Kandivali West, Mumbai (BMC)	2.32	1.95	3.75	2.60	4.46	10.83	12.96	97.43
Kasarvadavali, Thane (MPCB)	4.38	6.06	3.08	2.11	2.41	2.80	31.11	349.60
Katrap, Badlapur (MPCB)	8.11	11.68	3.35	2.15	1.99	2.24	13.04	351.88
Khadakpada, Kalyan (MPCB)	4.27	NE	4.32	NE	1.89	NE	181.5	NE
Khindipada-Bhandup West, Mumbai (IITM)	2.83	2.78	2.67	3.06	3.68	3.18	NR	NR
Kherwadi Bandra East, Mumbai (MPCB)	4.20	3.87	3.26	3.11	2.34	2.48	36.5	60.67
Kopripada Vashi, Navi Mumbai (MPCB)	5.18	4	4.56	2.68	2.05	2.72	9.97	118.67
Kurla, Mumbai (MPCB)	5.94	33.30	2.47	1.83	2.39	2.36	118.76	NR
Mahape, Navi Mumbai (MPCB)	7.26	6.65	3.83	2.82	1.66	2.02	NR	NR
Malad West, Mumbai (IITM)	NE	6.83	NE	2.31	NE	2.66	NE	22.63
Mazgaon, Mumbai (IITM)	4.47	6.68	3.64	2.16	2.45	2.91	10.82	22.74
Mindspace-Malad West, Mumbai (MPCB)	2.64	2.29	3.08	4.04	3.76	3.25	32.75	121.33
Bhayandar West, Mira-Bhayandar (MPCB)	3.95	2.68	4.03	3.35	2.28	3.12	16.5	124.63
Mulund West, Mumbai (MPCB)	4.24	178.91	2.49	1.58	2.80	2.90	176.31	54.67
Navy Nagar-Colaba, Mumbai (IITM)	9.86	9.03	2.39	2.16	2.54	2.66	11.61	20.46
Nerul, Navi Mumbai (MPCB)	5.37	NE	4.06	NE	1.91	NE	22.81	NE
Powai, Mumbai (MPCB)	3.40	NE	3.04	NE	2.65	NE	NR	NE
Sanpada, Navi Mumbai (MPCB)	6.04	4.14	2.83	5.40	2.20	1.88	39.28	24.75
Sector 2E Kalamboli, Navi Mumbai(MPCB)	5.78	5.35	3.47	2.51	1.99	2.48	26.63	91
Sewri, Mumbai (BMC)	3.32	4.36	2.81	2.90	3.37	2.82	21.34	14.07
Shivaji Nagar, Mumbai (BMC)	NE	6.17	NE	2.76	NE	2.37	NE	18.61
Siddharth Nagar-Worli, Mumbai (IITM)	NE	5.59	NE	2.24	NE	2.97	NE	26.71
Siddhivinayak, Ulhasnagar (MPCB)	22.81	16.54	2.42	2.04	2.12	2.22	14.04	NR
Sion, Mumbai (MPCB)	4.69	NE	3.42	NE	2.04	NE	185.97	NE
Tondare Taloja, Navi Mumbai (MPCB)	NE	4.92	NE	2.36	NE	2.74	NE	121.33
Upvan Fort, Thane (MPCB)	3.73	2.56	2.50	2.38	3.39	5.70	27.21	71.8
Vasai West, Mumbai (MPCB)	5.39	NE	2.43	NE	2.50	NE	364.84	NE
Vile Parle West, Mumbai (MPCB)	4.95	NE	2.52	NE	2.56	NE	90.29	NE
Worli, Mumbai (MPCB)	4.27	NE	2.32	NE	3.02	NE	350	NE
No. of stations less than 5 days	22	16	37	32	36	30	0	0

NE: Not Estimated due to insufficient data (>25 missing observations)
NR: Not revisited the state during the study period, SD: Standard Deviation

Table 5. Changes in Mean Return Time across monitoring stations (from 2024 and 2025)

AQI State	Number of Stations		Interpretation
	with increased Return time	with decreased Return time	
Good	11	17	Many stations depicts good air quality occurring frequently
Satisfactory	9	19	Strong stability with minor improvement
Moderate	18	9	Moderate air quality persist longer
Poor	16	5	Poor air quality but episodic

Mean first passage time of an AQI category

The Table 6 represents the Mean First Passage Time (MFPT) indicates the expected number of days required for the AQI category to move from one specified state to another state for the first time. Unlike, mean return time, which measures recurrence of same state, the MFPT represents the transitions between different air quality categories. The lower average values repre-

sents higher transitions, whereas higher values reflects slower transitions between states. It was observed that transitions from Moderate to Good and Poor to Good was occurred within 10 – 40 days, whereas transitions from Good to Moderate were relatively faster in 9 – 25 days followed by Good to Poor transition was observed exceeding 50 days indicating that the deterioration from good to poor was rare event.

Table 6. Mean first passage time for each monitoring station.

Air Quality Monitoring Station	Mean First Passage time (in days)							
	Moderate → Good		Poor → Good		Good → Moderate		Good → Poor	
	2024	2025	2024	2025	2024	2025	2024	2025
Bandra Kurla Complex, Mumbai (MPCB)	34.57	22.56	37.07	23.56	10.01	13.39	58.09	64.90
Bolinj, Virar (MPCB)	29.82	10.87	31.57	11.61	9.29	10.64	53.16	55.36
Borivali East, Mumbai (IITM)	NE	24.35	NE	27.35	NE	16.24	NE	378.47
Borivali East, Mumbai (MPCB)	10.07	NE	9.84	NE	18.40	NE	400.08	NE
Byculla, Mumbai (BMC)	15.63	14.89	17.06	11.28	18.66	19.73	67.19	193.01
Colaba, Mumbai (MPCB)	14.15	10.53	NR	5.58	15.63	21.44	NR	108.05
CBD Belapur, Belapur (MPCB)	29.08	26.87	30.08	24.61	11.73	25.19	193.23	89.46
Chhatrapati Shivaji Intl. Airport (T2), Mumbai (MPCB)	22.34	69.82	NR	NR	12.14	23.6	NR	NR
Chakala Andheri East, Mumbai (IITM)	23.05	24.36	24.43	27.36	14.61	10.97	64.78	118.28
Chembur, Mumbai (MPCB)	24.90	17.16	27.27	15.72	19.98	16.29	68.69	130.20
Ghatkopar, Mumbai (BMC)	19.72	28.93	21.44	NR	21.07	26.36	69.93	NR
Gokul Nagar, Bhiwandi (MPCB)	33.68	26.81	35.37	23.90	10.88	11.81	35.24	181.03
Kandivali East, Mumbai (MPCB)	24.02	NE	25.02	NE	11.25	NE	192.87	NE
Kandivali West, Mumbai (BMC)	15.28	9.02	17.88	9.80	23.03	36.59	54.12	214.09
Kasarvadavali, Thane (MPCB)	25.45	20.33	27.17	21.33	15.38	12.96	66.99	361.56
Katrap, Badlapur (MPCB)	32.06	29.99	34.06	21.11	12.31	14.00	36.38	352.76
Khadakpada, Kalyan (MPCB)	32.40	NE	33.40	NE	15.13	NE	195.63	NE
Khindipada-Bhandup West, Mumbai (IITM)	14.82	19.90	NR	NR	16.03	16.97	NR	NR
Kherwadi Bandra East, Mumbai (MPCB)	20.48	16.24	22.48	15.73	12.77	13.58	83.77	100.18
Kopripada Vashi, Navi Mumbai (MPCB)	30.21	14.73	31.91	15.73	13.79	9.63	27.99	127.30
Kurla, Mumbai (MPCB)	20.51	68.21	21.51	NR	9.68	10.6	127.44	NR
Mahape, Navi Mumbai (MPCB)	37.88	26.17	3.13	NR	15.23	13.28	NR	NR
Malad West, Mumbai (IITM)	NE	36.20	NE	38.20	NE	26.65	NE	69.90
Mazgaon, Mumbai (IITM)	17.15	20.86	19.30	22.77	9.21	17.96	32.84	121.34
Mindspace-Malad West, Mumbai (MPCB)	16.83	15.75	18.50	17.25	22.51	19.83	75.43	200.33
Bhayandar West, Mira-Bhayandar (MPCB)	37.75	17.20	38.50	13.96	19.91	23.89	41.93	199.69
Mulund West, Mumbai (MPCB)	12.13	183.32	13.13	185.32	10.07	10.5	185.38	117.83
Navy Nagar-Colaba, Mumbai (IITM)	29.85	23.67	31.78	25.80	10.32	15.38	28.95	56.74
Nerul, Navi Mumbai (MPCB)	26.26	NE	28.04	NE	10.53	NE	49.31	NE
Powai, Mumbai (MPCB)	23.52	NE	NR	NE	16.47	NE	NR	NE
Sanpada, Navi Mumbai (MPCB)	32.14	26.85	34.39	25.84	14.69	14.29	100.82	42.19
Sector 2E Kalamboli, Navi Mumbai(MPCB)	34.92	24.37	35.60	25.70	12.26	17.73	45.35	137.73
Sewri, Mumbai (BMC)	15.66	23.18	17.03	24.25	14.94	14.35	67.11	34.73
Shivaji Nagar, Mumbai (BMC)	NE	21.95	NE	24.32	NE	10.62	NE	52.45
Siddharth Nagar-Worli, Mumbai (IITM)	NE	20.43	NE	22.43	NE	14.71	NE	66.12
Siddhivinayak, Ulhasnagar (MPCB)	42.15	30.01	44.01	NR	10.24	11.90	34.46	NR
Sion, Mumbai (MPCB)	23.26	NE	9.91	NE	10.95	NE	186.75	NE
Tondare Taloja, Navi Mumbai (MPCB)	NE	16.36	NE	15.25	NE	12.23	NE	188.04
Upvan Fort, Thane (MPCB)	35.02	12.77	37.31	5.00	23.03	21.92	82.94	354.00
Vasai West, Mumbai (MPCB)	16.63	NE	17.63	NE	10.01	NE	373.85	NE
Vile Parle West, Mumbai (MPCB)	14.27	NE	8.13	NE	9.81	NE	94.19	NE
Worli, Mumbai (MPCB)	17.73	NE	18.73	NE	14.81	NE	363.81	NE

NE: Not Estimated due to insufficient data (>25 missing observations)

NR: Not revisited the state during the study period, SD: Standard Deviation

The Table 7 represents comparative analysis of air quality trends between 2024 and 2025 demonstrates that majority of the stations indicates improved recovery patterns with many stations transitioning faster from moderate and poor to good air quality. On the other

hand, majority of the stations suggest increased passage time for transitions from Good to moderate and poor air quality reflecting greater resistance to deterioration.

Table 7. *Changes in mean first passage time across monitoring stations from 2024 to 2025*

AQI State	Number of Stations with increased mean passage time from 2024 to 2025	Number of Stations with decreased mean passage time from 2024 to 2025	Interpretation
Moderate → Good	8	20	Faster recovery pattern in many stations
Poor → Good	4	17	Slight improvement in recovery from poor pollution
Good → Moderate	19	9	Good air remains persistent for longer period in many stations
Good → Poor	17	4	Strong increase in resistance to poor air quality.

Discussion

The present study utilized a discrete time Markov Chain process to analyse AQI transitions for the selected monitoring stations in MMR over the study period 2024 – 2025. In order to maintain the assumption of homogeneity in the transition probabilities, the modeling was implemented separately to each year. In addition to this, Markov chain model was implemented to analyse the distribution of the AQI level in the long term. A Markov Chain is commonly used in many fields because of its strong efficiency in predicting long run behaviour (Masseran, 2015). The Markov approach evaluates the probabilistic transitions between Good, Satisfactory, Moderate and Poor states, thereby providing in depth insight into persistence, recurrence and recovery dynamics of air quality. This modeling enables assessment of long term behaviour and short term transitions risk, thereby offering a quantitative analysis for achieving sustainable development goals. In this study, the steady state probabilities indicate that Moderate AQI remains dominant in long run across several monitoring stations. Such persistence may indicate that continued influence of factors such as vehicular emissions, industrial activities and construction work may contribute to increase in concentration of particulate matter. However, when we compare 2024 and 2025, a notable reduction was observed in the Poor category from 4% to 2% depicting a decline in long run recurrence of extreme level of air pollution. This suggests that although, moderate level of air pollution persists for longer period of time, less severe level of air pollution was observed in the year 2025. The mean return time fur-

ther supports the steady state probabilities. In 2025, the poor level of air pollution took significantly longer to recur as compared with 2024. In addition to that satisfactory level of air pollution reappeared more regularly than 2024. This indicates that extreme level of air pollution became less frequent in the subsequent year and good and satisfactory level exhibited more frequent reoccurrence of favourable air quality conditions. Instead of saying that overall air quality has improved, the Markov measures demonstrate that 2025 exhibited enhanced resilience, slower deterioration and less severe cases than previous year. The findings have major impact for environmental management. In recent years, a Graded Response Action plan (GRAP) was introduced for National Capital Region (NCR) and adjoining areas (GRAP Plan for Air Quality Curtail, 2024) to combat severe air pollution. This plan was formulated by Supreme Court in 2016 and is implemented by the Commission for Air Quality Management. It was clearly stated in the plan that if AQI moves to poor quality level then the action was taken to ban construction activities, halting non-essential vehicles, heavy duty truck entry, introduced odd-even vehicle schemes and promoted explicit use of public transport. This step by step action was implemented till the air quality deteriorates back to satisfactory level of air pollution. The transition based analytics developed in this study provides a quantitative analysis for strengthening such policies. For example, if the probability of transition of Moderate to Poor state increasing beyond a defined threshold level then precautionary actions can be taken even before the AQI official enters into poor category. This approach

shifts decision making from threshold based reaction to probability based prevention. Using the findings, the Markov modeling can provide a proposed threshold range represented in Table 8 for implementing such action plans. The proposed threshold range depicted in table 8 were estimated using empirical quartiles of the Markov chain indicators estimated during 2025 across all monitoring stations The third quartile (Q_3) was used

to identify thresholds associated with steady state probabilities for the moderate and poor AQI states, whereas the first quartile (Q_1) was used to identify thresholds reflecting frequent recurrence and rapid deterioration in air quality. These thresholds provides statistically robust and study based decision criteria for air quality monitoring, early warning and AQI management strategies.

Table 8. *Proposed threshold range for AQI and recommended action*

Markov model Indicator	Statistical measure	Proposed threshold range (Study Based)	Recommended action	Objective
Steady state-Moderate	Long run robability	>41%	Traffic management, dust control	Reduce persistent pollution
Steady state- Poor	Long run robability	>3.5%	Activate emergency control measures	Prevents extreme pollution
MRT Moderate	Mean Recurrence evel	<=2.4 days	Weekly prevention of dust suppression and traffic control	Breaks pollution persistence cycle
MFPT Good - Poor	Mean First Passage Time	< 68 days (approximately 2 months)	Strengthens early activation of GRAP measures	Prevents sudden increase in AQI

Therefore, implementing Markov transition probabilities into real time air quality dashboards can support graded action plans and support risk based decision modelling. This indicates that strict action plan need not be implemented when the air quality conditions is in stable conditions. Instead a more focused approach can be adopted, where interventions can be applied to monitoring stations that shows higher chance of air quality deterioration. Hence for such stations, precautionary measures can be taken before the air quality enters into poor category. The Short term probabilistic forecasting can provide an early warning of pollution levels that enhances warning system. This approach can support risk based decision making. Such a probabilistic based decision making model reduces unnecessary economic disruption but still ensures adequate environment protection. The findings suggested an improvement in AQI in the year 2025, continued dominance of Moderate level of air quality underscores the need for sustained structural interventions. These findings therefore resembles the progress in air quality, but this cannot be termed as complete environmental recovery.

Conclusions

This study used a discrete-time Markov chain model to understand how air quality changes over time across monitoring stations in the Mumbai Metropolitan Region during 2024 and 2025. Rather than only describing

pollution levels, the analysis examined on AQI state transitions from one state to another, on an average duration they tend to persist, and how quickly the air quality improves or worsen. This provides a better understanding of air quality behaviour. The results show that Moderate air quality remains throughout in majority of the monitoring stations, suggesting that the emission from sources like traffic, industries, and construction activities continue to influence pollution levels. However, a comparison between the two years indicates that 2025 experienced a slight improvement in air quality as compared to 2024. The poor state of AQI became less frequent, recovery from moderate conditions occurred more quickly as compared to 2024. Beyond statistical findings, the study demonstrates the practical application of transition-based analysis to air quality assessment. Instead of depending on constant AQI thresholds in order to impose measures like construction restrictions, the Markov chain framework provides probability-based insights that can help authorities to identify the deterioration risks in advance. This allows for more timely and targeted interventions with reducing unnecessary disruptions.

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