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Dynamic System Modeling of $PM_{2.5}$ Emissions and Concentrations in DKI Jakarta Based on BAU, Moderate, and Aggressive Scenarios

Chairil Linggabinangkit
Teknologi Sepuluh Nopember, Indonesia

Joni Hermana
Teknologi Sepuluh Nopember, Indonesia

***Corresponding author:**
Chairil Linggabinangkit, Teknologi Sepuluh Nopember, Indonesia.
✉ chairil.linggabinangkit@gmail.com

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Abstract

Background: Rapid urbanization, increasing motor vehicle use, and high dependence on fossil-based energy sources have contributed to persistently elevated $PM_{2.5}$ concentrations. Although various policies have been implemented, their long-term effectiveness under different intervention levels has not been sufficiently evaluated using an integrated and dynamic approach.
Objective: This study aims to develop a system dynamics model to project $PM_{2.5}$ emissions and concentration trends in DKI Jakarta up to 2040 under three scenarios: Business as Usual (BAU), Moderate, and Aggressive intervention.
Method: A system dynamics modeling approach was employed by integrating key variables, including motor vehicle growth, electric vehicle (EV) adoption, electricity consumption, renewable energy penetration, and industrial activity. The model was calibrated using historical data from 2018 to 2023. Three scenarios were simulated: BAU without additional intervention, Moderate with approximately 20% EV penetration and a 30% renewable energy mix, and Aggressive with EV penetration of ≥50% and a renewable energy mix of ≥70%.
Result: Under the BAU scenario, $PM_{2.5}$ concentrations decline only marginally (approximately ±40% by 2040). The Moderate scenario achieves approximately ±60% reduction, though insufficient to meet optimal air quality standards. The Aggressive scenario demonstrates the most substantial impact, with reductions reaching approximately ±80%.
Conclusion: Aggressive policy interventions combining high EV penetration and substantial renewable energy adoption are essential for significant $PM_{2.5}$ reductions in DKI Jakarta. System dynamics modeling provides a robust framework for evaluating long-term air quality policies and supporting evidence-based decision-making.

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INTRODUCTION

Air pollution from fine particulate matter with an aerodynamic diameter of ≤2.5 µm ($PM_{2.5}$) is one of the most serious environmental and health problems in densely populated urban areas (Zieliński et al., 2018). Exposure to $PM_{2.5}$ has been shown to be significantly correlated with an increased risk of cardiovascular disease, chronic respiratory disorders, and premature death. The World Health Organization has set an annual $PM_{2.5}$ threshold of 5 µg/m^3, but most large cities in developing countries still far exceed this value.

Globally, ambient $PM_{2.5}$ air pollution was responsible for approximately 4.2 million premature deaths in 2019, with the burden disproportionately affecting low- and middle-income countries in Asia and Africa, where rapid urbanization and industrialization continue to intensify emissions. This phenomenon underscores the urgent need for evidence-based policy interventions that can effectively mitigate air pollution while supporting sustainable urban development.

DKI Jakarta has consistently been recorded as one of the regions with the worst air quality in Southeast Asia. Air quality monitoring data from 2018–2023 show that the average annual $PM_{2.5}$ concentration is in the range of 35–50 μg/m^3, or 7–10 times higher than WHO guidelines. This condition is also reflected in the Air Quality Index (AQI), where Jakarta periodically falls into the unhealthy to very unhealthy category, especially during the dry season. This fact confirms that the $PM_{2.5}$ problem in Jakarta is structural and chronic, not just an episodic phenomenon. The persistence of elevated $PM_{2.5}$ levels despite existing regulatory frameworks indicates fundamental limitations in current policy approaches and implementation mechanisms.

The main sources of $PM_{2.5}$ emissions in Jakarta come from the fossil fuel–based transportation sector, fossil fuel–based electricity generation, and industrial activities. Previous research has documented various aspects of this complex problem. Islam (2023) conducted spatio-temporal analysis of $PM_{2.5}$ concentrations across Southeast Asian megacities and identified transportation and biomass burning as dominant sources, while emphasizing the need for integrated regional management strategies.

Lestari (2022) quantified emission sources in Jakarta using receptor modeling and found that vehicular emissions contributed approximately 24% of total $PM_{2.5}$, with significant contributions also from industrial sources and power plants. Syuhada (2023) examined the economic valuation of health impacts from air pollution in Jakarta, estimating annual health costs exceeding USD 1 billion, highlighting the substantial economic burden beyond direct mortality and morbidity. Furthermore, Molina (2020) reviewed air quality management policies across Asian megacities and emphasized that fragmented, sector-specific approaches have consistently failed to achieve meaningful long-term improvements.

However, current air pollution control policies tend to be sector-specific and short-term, thus failing to produce significant and sustainable reductions in $PM_{2.5}$ concentrations. These policies often operate in isolation transportation policies rarely account for electricity demand implications, while energy policies seldom consider induced changes in mobility patterns or industrial behavior. Static policy evaluations and conventional econometric approaches, while useful for establishing correlations, cannot adequately capture the dynamic feedback loops, time delays, and nonlinear interactions between transportation systems, energy infrastructure, industrial activities, and resultant air quality outcomes. Such approaches also struggle to model policy implementation lags, behavioral adaptation, and cumulative long-term effects that are critical for effective air quality management.

System dynamics modeling offers a framework specifically designed to capture feedback mechanisms, stock-flow relationships, and temporal delays inherent in socio-technical-environmental systems. Recent applications in Southeast Asia demonstrate its utility for integrated policy analysis. Toh (2025) employed system dynamics to evaluate low-carbon transportation scenarios in Kuala Lumpur, revealing how feedback between vehicle fleet composition, fuel consumption, and policy incentives shapes emission. Similarly, Vu (2020) developed a system dynamics model for urban water and air quality management in Ho Chi Minh City, demonstrating the interconnectedness of infrastructure development, population growth, and environmental degradation. These studies highlight the regional relevance and analytical power of system dynamics for addressing urban environmental challenges in Southeast Asian contexts, yet no comparable integrated modeling framework has been applied specifically to Jakarta's $PM_{2.5}$ problem.

Therefore, a modeling approach is needed that can represent the dynamic interactions between sectors, the effects of policy feedback, and the long-term implications for air quality, which cannot be captured by conventional static statistical approaches. The novelty of this research lies in its integrated, feedback-oriented approach that explicitly contrasts with static or sectoral econometric methods by capturing how policy interventions in one sector generate ripple effects across others over time, enabling evaluation of synergistic and antagonistic policy interactions that conventional approaches cannot reveal. The research objectives are: first, to construct a validated system dynamics model representing $PM_{2.5}$ generation and dispersion mechanisms in Jakarta; second, to simulate and compare the effectiveness of alternative policy scenarios, including transportation electrification, renewable energy transition, and industrial emission controls; and third, to identify policy combinations that achieve the greatest $PM_{2.5}$ reduction with consideration of implementation feasibility and co-benefits.

The research benefits are to provide an evidence-based decision support tool for designing integrated air quality interventions and to contribute methodologically by demonstrating the application of system dynamics to urban air quality management in a data-constrained developing country context. In addition, this research empowers stakeholders with analytical capacity to move beyond fragmented, reactive approaches toward proactive, systems-oriented air quality management that aligns with sustainable urban development goals and protects public health in one of Southeast Asia's largest and most polluted megacities.

METHOD

Dynamic Systems Modeling Framework

The dynamic system modeling framework in this study was developed to represent the structural relationships and feedbacks between human activities, energy–transportation policies, $PM_{2.5}$ emissions, and ambient $PM_{2.5}$ concentrations in DKI Jakarta. The conceptual structure of the model was developed using a causal loop diagram (CLD) as an initial tool to identify causal relationships and nonlinear dynamics between key variables in the urban air quality system.

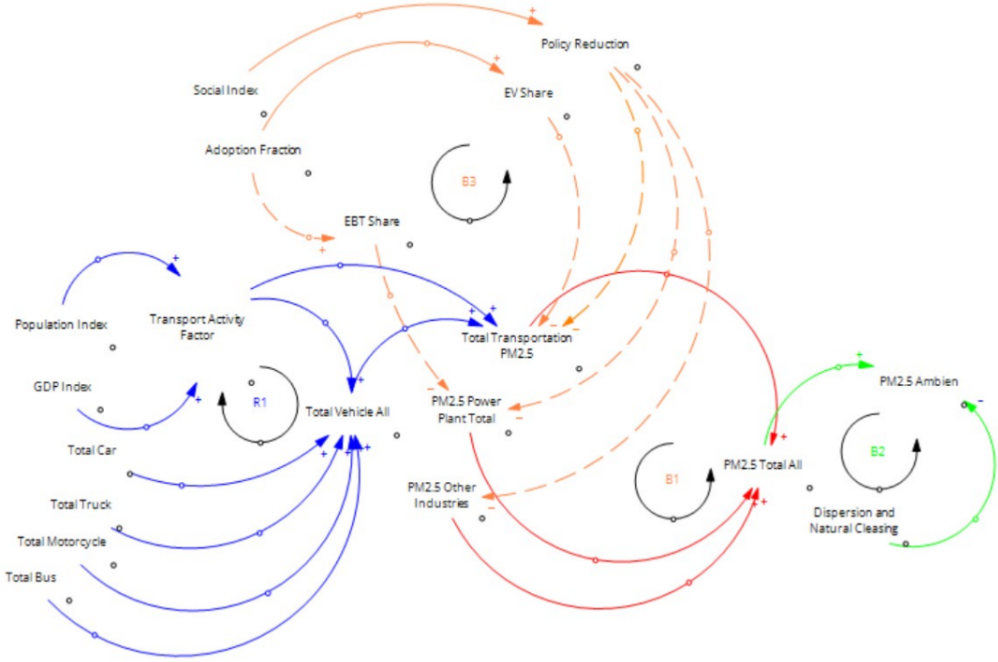

Figure 1. Causal Loop Diagram of the Dynamic System Model used

Figure 1 shows the CLD of the dynamic $PM_{2.5}$ system, which consists of four main subsystems, namely: (1) the transportation activity and vehicle growth subsystem, (2) the electric vehicle policy and adoption subsystem, (3) the energy and electricity generation subsystem, and (4) the ambient air quality and natural cleansing of the atmosphere subsystem. In the transportation subsystem, the growth in the number of motorized vehicles is influenced by the increase in population and Gross Regional Domestic Product (GRDP), which is represented by the Population Index and GDP Index. Both variables increase the Transport Activity Factor, which in turn drives an increase in the total number of vehicles (cars, motorcycles, buses, and trucks). This mechanism forms a reinforcing loop R1, where economic and demographic growth strengthens transportation activities and increases $PM_{2.5}$ emissions from the transportation sector in a sustained manner if not balanced by control policies.

The policy subsystem is modeled through the variables EV Share, Adoption Fraction, and Social Index, which represent the role of government policy and social acceptance in electric vehicle adoption. Increasing electric vehicle adoption reduces the proportion of fossil-fueled vehicles, thereby reducing $PM_{2.5}$ emissions from the transportation sector. This relationship forms a balancing loop B3, which functions to suppress the growth of transportation emissions in response to electrification policy interventions.

In addition to the transportation sector, the energy and electricity generation subsystem is modeled through the variables Renewable Energy Share and $PM_{2.5}$ Power Plant Total. Increasing the renewable energy mix reduces the electricity generation emission factor, thereby preventing an increase in $PM_{2.5}$ emissions due to increased electricity demand, including from the electric transportation sector. The interaction between the increase in EVs and the share of renewable energy is interrelated and determines the systemic effectiveness of the policy.

All $PM_{2.5}$ emissions from the transportation, power generation, and other industrial sectors are accumulated in the $PM_{2.5}$ Total All variable, which then affects the Ambient $PM_{2.5}$ concentration. This concentration is then reduced through the natural atmospheric dispersion and cleansing process, modeled as the balancing loop B2. This loop represents the natural mechanism of the environmental system in reducing pollutant concentrations, although its capacity is limited and unable to offset the ever-increasing emissions without policy intervention. Thus, the CLD in Figure 1 shows that the dynamics of $PM_{2.5}$ in DKI Jakarta are controlled by complex interactions between reinforcing loops that drive increased emissions and balancing loops that seek to reduce emissions through policies and natural processes.

$PM_{2.5}$ Emission and Concentration Formulation

Total $PM_{2.5}$ emissions were calculated as the accumulated emissions from the transportation, power generation, and other industrial sectors. Mathematically, total $PM_{2.5}$ emissions were formulated as:

$$E\_PM_{2.5}(t) = E\_trans(t) + E\_pl(t) + E\_ind(t) \tag{2-1}$$

Transportation sector emissions were calculated based on the number of vehicles, vehicle kilometers traveled (Vehicle Kilometers Traveled/VKT), and emission factors as follows:

$$E\_trans(t) = \Sigma\, [\, N\_i(t) \times VKT\_i(t) \times EF\_i\,] \tag{2-2}$$

where N_i is the number of vehicles of type i, VKT_i is the annual mileage, and EF_i is the $PM_{2.5}$ emission factor.

Ambient $PM_{2.5}$ concentrations were derived from total emissions by considering the air volume of the study area and the natural cleaning factor of the atmosphere:

$$C\_PM_{2.5}(t) = (\, E\_PM_{2.5}(t) \times 10\text{^}12\,) \,/\, (\, A \times H \times v \times 31{,}536{,}000\,) \times K \tag{2-3}$$

where $C\_PM_{2.5}$ is the $PM_{2.5}$ concentration (μg/m^3), A is the area (m^2), H is the air mixing height (m), v is the wind speed (m/s) and K is the natural cleaning coefficient.

Parameter Assumption Justification

To ensure the physical realism of the emission–concentration transformation, several key atmospheric parameters were defined based on empirical literature and urban air dispersion studies.

The air mixing height (H) represents the vertical layer within which pollutants are dispersed. In this study, the mixing height was assumed to range between 300–800 m, reflecting typical tropical urban boundary layer conditions. Previous atmospheric studies in Southeast Asian megacities indicate that mixing height varies diurnally and seasonally, with lower values during stable atmospheric conditions that tend to trap pollutants near the surface.

The wind speed (v) parameter plays a critical role in horizontal pollutant dispersion. An annual average wind speed of 1.5–2.5 m/s was applied in the model, consistent with meteorological observations for Jakarta's coastal–urban climate. Lower wind speeds are associated with reduced dispersion capacity and higher pollutant accumulation.

The natural cleansing coefficient (K) represents combined atmospheric removal processes, including dry deposition, wet deposition, and chemical transformation. Due to the absence of a single measurable indicator, this coefficient was treated as an aggregated environmental removal factor. Values were derived and calibrated from previous urban air quality system dynamics models and adjusted to reproduce historical $PM_{2.5}$ concentration patterns. These parameter assumptions are widely used in simplified box-model air quality formulations and are considered appropriate for long-term policy simulation rather than short-term forecasting.

Uncertainty and Sensitivity Analysis

Given the inherent uncertainty in atmospheric processes and long-term policy projections, a limited sensitivity analysis was conducted to evaluate the robustness of the model results. Sensitivity simulations were performed by varying one parameter at a time while holding others constant (*ceteris paribus* approach). The results indicate that $PM_{2.5}$ concentration outcomes are most sensitive to variations in mixing height and emission factors, while wind speed and cleaning coefficients show moderate influence on concentration changes. Despite these uncertainties, the overall policy response patterns—particularly the comparative effectiveness between BAU, Moderate, and Aggressive scenarios—remain structurally consistent. This indicates that the model is sufficiently robust for scenario-based policy analysis, even under parameter variability.

Policy Scenario

The development of policy scenarios in this study is based on a scenario-based policy analysis approach commonly used in dynamic systems studies and urban air quality modeling. This approach allows for the evaluation of system responses to different levels of policy intervention and identifies thresholds for policy effectiveness in reducing emissions and pollutant concentrations (Sterman, 2002);(Forrester, 1961). In the context of $PM_{2.5}$ control, several previous studies have emphasized that air quality improvements cannot be achieved through a single sector alone but require a combination of integrated transportation and energy policies (Hao et al., 2017);(Mehlig et al., 2021).

In particular, transportation electrification has been widely studied as a key strategy to reduce particulate emissions in urban areas. However, various studies have shown that the environmental benefits of electric vehicles are highly dependent on the structure of the electricity system that supplies the energy. Gryparis (2020) show that increasing electric vehicle penetration without a corresponding increase in the renewable energy mix has the potential to lead to an emission-shifting phenomenon, namely a shift in emissions from the transportation sector to the electricity generation sector. Therefore, recent literature emphasizes the importance of integrated policy scenarios that combine electric vehicle adoption and energy sector decarbonization to achieve optimal air quality benefits (Hao et al., 2017).

Based on this framework, this study develops three policy scenarios, namely BAU, Moderate, and Aggressive, which represent different levels of policy intervention intensity. The BAU scenario represents a baseline condition without significant policy additions beyond historical trends. In this scenario, motor vehicle growth is primarily driven by population growth and Gross Regional Domestic Product (GRDP), while electric vehicle penetration and the increase in the renewable energy mix occur slowly following natural market adoption. The BAU approach is widely used in system dynamics studies as a baseline to evaluate the effectiveness of alternative policies, as it reflects realistic conditions without intervention (Schünemann et al., 2024).

The Moderate scenario is designed to represent a relatively realistic, implementable, and gradual policy intervention, assuming electric vehicle penetration of around 20% and a renewable energy mix of around 30%. This moderate approach aligns with several air quality policy modeling studies showing that moderate interventions can curb emissions growth but are not necessarily sufficient to produce significant absolute reductions in $PM_{2.5}$ concentrations (Hao et al., 2017). From a systems dynamics perspective, the moderate scenario is generally able to weaken the reinforcing loop of emissions growth but still does not fully offset the reinforcing feedback from growth in economic activity and transportation.

The aggressive scenario represents a high-intensity policy intervention, assuming electric vehicle penetration of ≥50% and a renewable energy mix of ≥70%. The literature suggests that an ambitious scenario is needed to break the reinforcing loop in rapidly expanding urban transportation systems, particularly in large, highly motorized cities like Jakarta. These studies indicate that consistent long-term reductions in $PM_{2.5}$ concentrations are generally achieved only when transportation electrification parallels decarbonization of the electricity generation sector. Therefore, the aggressive scenario in this study is positioned as an upper bound on the effectiveness of $PM_{2.5}$ control policies.

The three scenarios were then integrated into a system dynamics model by changing parameters for electric vehicle adoption, the share of renewable energy, and policy emission reduction factors. With this approach, scenario evaluation captures not only partial sectoral impacts but also cross-sectoral interactions and synergistic effects between transportation and energy policies, as recommended in the system dynamics and urban air quality policy literature (Sterman, 2002).

Data and Model Calibration

IQAir historical data from 2018–2023 was used as the basis for developing, calibrating, and validating a dynamic system model, which included ambient $PM_{2.5}$ concentration data in DKI Jakarta. Studies by Kusumaningtyas (2021) showed that annual $PM_{2.5}$ concentrations in Jakarta consistently ranged from 30–50 μg/m^3, with interannual variations influenced by transportation, industrial activities, and meteorological conditions.

Data on the number of motorized vehicles and their growth were obtained from the Central Statistics Agency (BPS) of DKI Jakarta. A similar approach was used by Ghaffarpasand (2020) in their inventory of motorized vehicle emissions in urban areas. Data on electricity consumption and energy mix were obtained from national energy reports and emissions inventory studies in the electricity sector, which refer to the methodology of the Intergovernmental Panel on Climate Change (IPCC, 2019).

Model calibration is performed by adjusting key parameters, such as emission correction factors and atmospheric natural cleaning coefficients, so that the simulation results are able to represent the historical behavior of the system. This calibration approach refers to the principle of behavior reproduction test in dynamic system modeling, as explained by John D. Sterman (2002), where the main goal of calibration is to ensure the appropriateness of the pattern and direction of change of the main variables, not an absolute numerical match.

This standard also aligns with the practice of dynamical system-based air quality modeling in previous studies, which use a combination of statistical indicators and trend evaluation to assess the model's suitability as a long-term policy analysis tool. Therefore, the calibration process in this study follows a widely accepted approach in the environmental dynamical system modeling literature.

RESULTS AND DISCUSSION

Results

Validation of Dynamic System Models

Model validation is a crucial step in assessing the ability of a dynamic system model to represent the historical behaviour of a real system. In this study, validation was conducted by comparing simulated ambient $PM_{2.5}$ concentrations with observed data for the 2018–2023 period. This approach aims to evaluate trend matching between model output and actual data, not to produce identical numerical predictions.

Behavior reproduction test- based validation approach is a common practice in dynamic systems modeling, as stated by Forrester (1961) and Sterman (2002), who emphasized that the primary goal of a policy dynamic systems model is to represent the system's behavior structurally and temporally, rather than to maximize short-term numerical accuracy. Therefore, validation in dynamic systems places more emphasis on the similarity of trend direction, turning points, and system response to policy changes, rather than the deterministic conformity of annual values.

The model fit level is evaluated using two statistical indicators, namely the Pearson correlation coefficient (r) and the Root Mean Square Error (RMSE). The use of this combination of correlation and absolute error indicators has been widely applied in research on air quality and environmental dynamic systems, because it is able to capture two complementary aspects of validation: the similarity of temporal patterns and the magnitude of numerical deviations.

The r coefficient is used to measure the strength of the linear relationship between simulation results and observational data, thus representing the model's ability to capture $PM_{2.5}$

trend dynamics over time. Meanwhile, the RMSE is used to measure the mean absolute error, which provides a quantitative measure of the closeness of simulation results to observed values.

A similar validation approach was also used in studies of air quality dynamics systems in urban areas by Ren (2020), who evaluated model performance based on the fit of pollutant concentration trends and RMSE values relative to the range of historical data variations. These studies showed that moderate to strong correlation values, although not perfect, are still acceptable as long as the model is able to reproduce the main change patterns and system responses to policy scenarios. This is in line with the findings of Averchenkova (2020) who stated that in environmental systems influenced by many external factors, achieving perfect correlation is rare and not a prerequisite for policy model validity.

Table 1. Validation results of the $PM_{2.5}$ dynamic system model using Pearson correlation coefficient and RMSE

Scenario	**Pearson Correlation Coefficient (r)**	**RMSE (μg/m^3)**
SMELL	−0.507	12.02
Moderate	−0.494	8.60
Aggressive	−0.475	5.03

Source: processed data

The validation results indicate that all scenarios produce Pearson correlation coefficient (r) values within the moderate relationship range in absolute terms, accompanied by relatively small RMSE values compared to the observed annual variation in $PM_{2.5}$ concentrations. It is important to clarify that the negative sign of the correlation coefficients does not indicate poor model performance.

Instead, it reflects an inverse directional relationship between simulated and reference datasets in certain temporal phases. In system dynamics validation, the strength of pattern reproduction is evaluated based on the absolute value ($|r|$) rather than the sign of the coefficient. Therefore, correlation values of −0.507, −0.494, and −0.475 still indicate moderate agreement in reproducing temporal trends.

Based on interpretation criteria commonly used in environmental studies and system modeling, an $|r|$ value of 0.40–0.59 is categorized as a moderate relationship, while $|r| \geq 0.60$ is considered strong (Mukaka, 2012). Thus, the correlation values obtained in this study indicate that the model can represent the temporal pattern of $PM_{2.5}$ adequately to well, although it does not achieve perfect correlation.

Furthermore, the RMSE values obtained across all scenarios are relatively low compared to the amplitude of annual $PM_{2.5}$ concentration variations. This RMSE-based evaluation approach relative to the data range is widely used in air quality modeling studies, where a model is considered to perform well if the RMSE value is below 20–30% of the range or mean of observed concentrations (Willmott & Matsuura, 2005);(Chai & Draxler, 2014). In the context of this study, RMSE values well below this threshold indicate that the model's numerical deviation is still within acceptable limits for policy analysis.

The consistent pattern of decreasing RMSE from the BAU scenario to the Moderate and Aggressive scenarios indicates that the model structure is increasingly capable of representing system dynamics when policy variables are explicitly included. This phenomenon aligns with the findings of de la Torre (2026) which show that policy-based air quality models tend to have better validation performance when structural interventions such as transportation electrification and electricity generation decarbonization are explicitly modeled, compared to scenarios without policies.

The combination of moderate to strong Pearson correlation values and relatively small RMSE values supports the conclusion that the model has adequate behavioural validity. This is consistent with validation standards in policy dynamic systems modeling, where model success is judged by its ability to capture system patterns and responses to interventions, rather than by a perfect numerical fit to historical data (Sterman, 2002).

Although correlation values in some scenarios do not perfectly approach one, these results are still acceptable in the context of modeling policy dynamics systems. Sterman (2002) emphasized that very high numerical correlations do not necessarily indicate a structurally sound model, as they may reflect overfitting to historical data. In this study, moderate correlation values indicate that the model is capable of capturing general system behavior without losing its exploratory capabilities in evaluating long-term policy scenarios.

Discussion

Scenario Simulation Results

The transportation sector is a major contributor to $PM_{2.5}$ emissions in DKI Jakarta, primarily from fossil-fueled motor vehicles. In the developed dynamic system model, the adoption of EVs is modeled as a structural variable that directly reduces the number of active conventional vehicles. The reduction in transportation emissions occurs through the substitution mechanism of conventional vehicles by electric vehicles, so that transportation emissions are formulated as a function of the number of conventional vehicles, vehicle mileage, and emission factors.

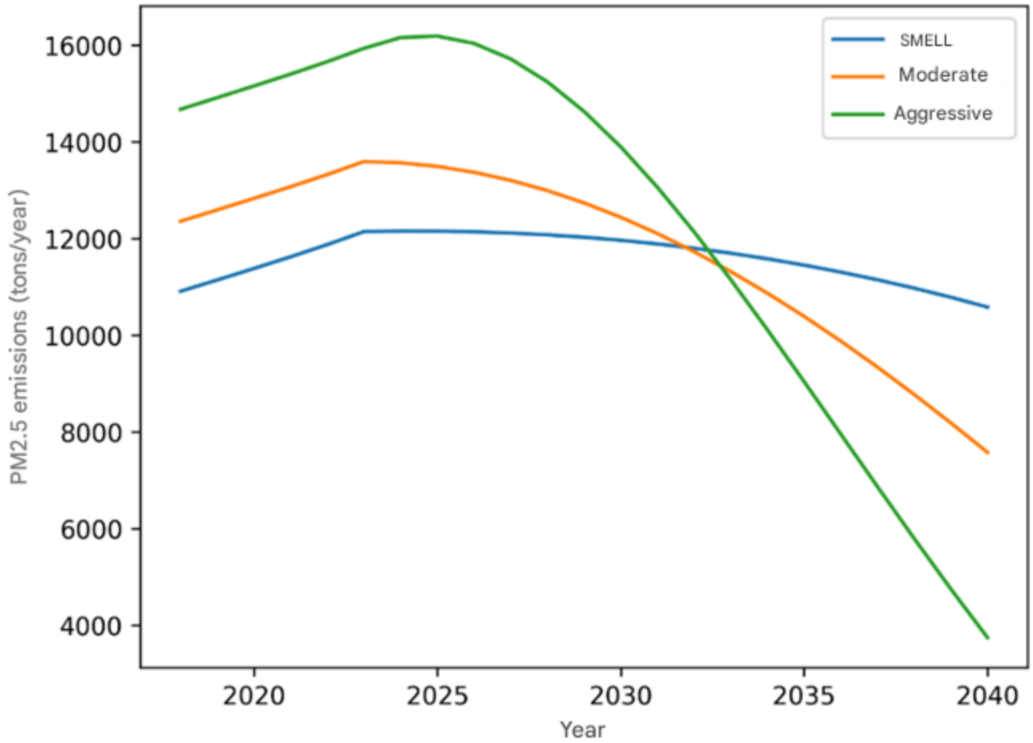

Figure 2. Total $PM_{2.5}$ emissions in the BAU, Moderate, and Aggressive scenarios.

In the BAU scenario (Figure 2), $PM_{2.5}$ emissions show a relatively stable trend until the beginning of the projection period and only experience a limited decline towards the end of the period. This pattern reflects the continued high dominance of fossil-fuelled motor vehicles due to the growth of transportation activities driven by population and GRDP increases, as also reported in the urban emissions inventory study in Asia by (Velamuri et al., 2024).

In the Moderate scenario, the $PM_{2.5}$ emission trend begins to show a more pronounced decline after the middle of the simulation period. This is related to the penetration of electric vehicles, which reaches around 20%, gradually reducing the number of active conventional vehicles. However, the emission decline is gradual and not yet significant in absolute terms at this initial stage, indicating that the moderate level of electric vehicle penetration is not yet sufficient to fully counteract the reinforcing effect of transportation activity growth. This finding is consistent with the research of Hao (2017), which showed that moderate levels of electric vehicle adoption are more effective in curbing emissions growth than producing a sharp decline.

In contrast, in the Aggressive scenario, $PM_{2.5}$ emissions show a sharp and consistent decline after peaking early in the projection period. This decline reflects the massive substitution of conventional vehicles with electric vehicles when EV penetration reaches ≥50%. This pattern is consistent with the findings of Bayani (2022), who showed that a significant impact of transportation electrification on particulate matter emissions is only apparent when EV penetration exceeds a certain critical threshold.

The Impact of Renewable Energy on $PM_{2.5}$ Emissions in the Power Generation Sector

As shown in Figure 3, the dynamics of total $PM_{2.5}$ emissions from all sources show clear differences in trajectories across policy scenarios. In the *Business as Usual* (BAU) scenario, $PM_{2.5}$ emissions from the electricity generation sector show a gradual upward trend until around 2031, before experiencing a relatively small decline until the end of the simulation period. This pattern reflects the energy mix, which is still dominated by fossil-fuelled power plants, where increasing electricity demand is not offset by a significant reduction in emissions. This finding is consistent with the results of an inventory of electricity generation emissions in developing countries reported by (Roy et al., 2021).

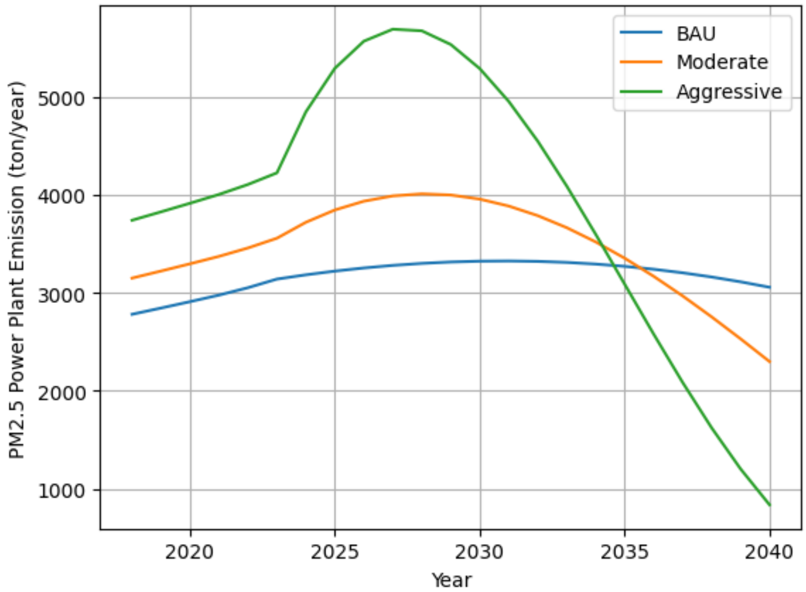

Figure 3. Projection of Total $PM_{2.5}$ Emissions from Power Plants in BAU, Moderate, and Aggressive Scenarios (2018–2040)

In the Moderate scenario, $PM_{2.5}$ emissions from the power generation sector increase until the late 2020s, then begin to decline gradually after 2030. This decline indicates the initial impact of increasing the renewable energy mix to around 30%, which can reduce the emission intensity of power generation despite continued increases in energy demand. A similar pattern was also reported by Hao (2017), who showed that partial energy transitions generally result in stabilization or gradual reductions in emissions, especially in power systems that were previously heavily dependent on fossil fuels.

In contrast, in the Aggressive scenario, $PM_{2.5}$ emissions from the power generation sector exhibit a more dynamic pattern, with an initial increase in emissions due to rising electricity demand—including from the adoption of electric vehicles—followed by a sharp and consistent decline midway through the simulation period. This drastic decline reflects the increase in the renewable energy mix to ≥70%, which significantly lowers the power generation emission factor and displaces fossil fuel generation in meeting energy needs. These results align with the findings of Tian (2023), which emphasize that the air quality benefits of transportation electrification can only be optimally achieved when accompanied by decarbonization of the power generation sector.

Interaction of Electric Vehicles in Dynamic Systems

The interaction between electric vehicle adoption and $PM_{2.5}$ emission reduction is clearly visible when comparing the three scenarios simultaneously. In the Moderate scenario, despite a significant increase in the number of electric vehicles (Figure 4), the reduction in $PM_{2.5}$ emissions is relatively limited because the electricity emission factor remains quite high. This situation indicates a partial decoupling between vehicle growth and emission reduction.

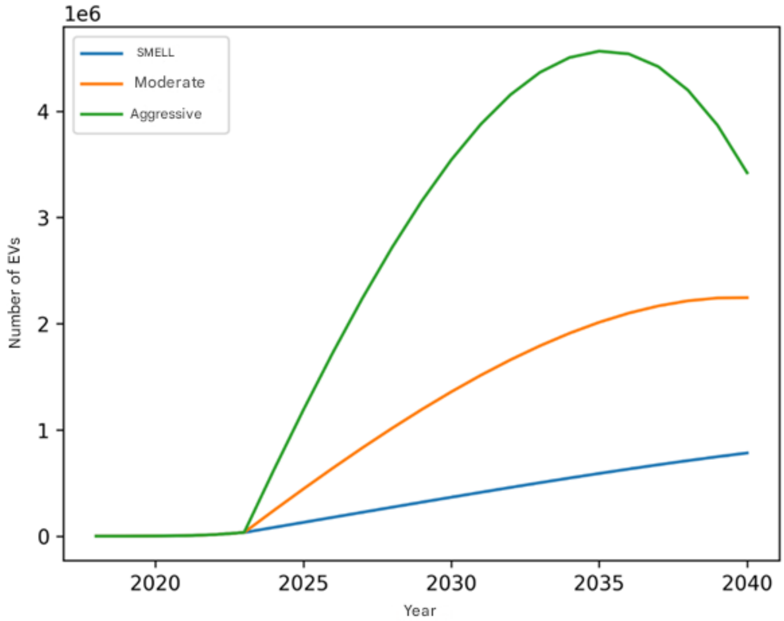

Figure 4. Growth in the number of electric vehicles in each scenario

In contrast, in the Aggressive scenario, the combination of high EV penetration and a large renewable energy mix produces a strong synergistic effect. The reduction in $PM_{2.5}$ emissions stems not only from reduced vehicle exhaust emissions but also from reduced upstream emissions in the electricity generation sector. This pattern is consistent with the conceptual framework of integrated energy–transport policy proposed by Wiedemann (2022), where the effectiveness of air quality policies is determined by cross-sectoral integration.

Impact of Emission Reduction on Ambient $PM_{2.5}$ Concentration

In the BAU scenario (Figure 5), $PM_{2.5}$ concentrations experienced only a limited decrease and tended to stagnate at around 28–32 μg/m^3, still well above WHO guidelines. This reflects the inability of the atmosphere's natural cleansing mechanisms to keep pace with the relatively high emission rate.

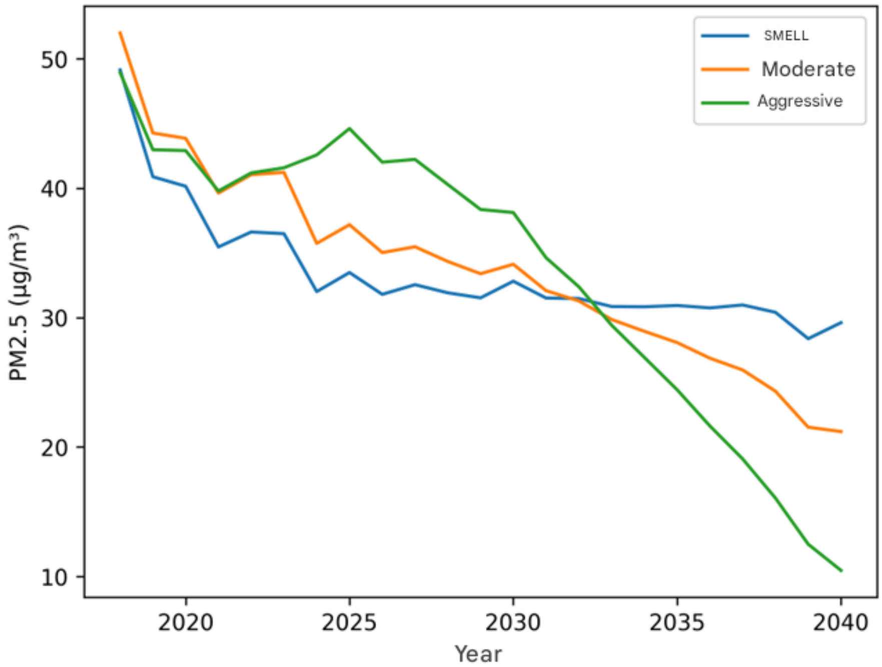

Figure 5. Ambient $PM_{2.5}$ concentration in BAU, Moderate, and Aggressive scenarios.

In the moderate scenario, $PM_{2.5}$ concentrations showed a clearer downward trend but remained above the health threshold until the end of the simulation period. This is consistent with the findings of Wang (2020), which showed that partial policies generally only resulted in moderate improvements in air quality in large cities with high emission source complexity. In contrast, in the Aggressive scenario, $PM_{2.5}$ concentrations declined sharply, approaching 10–15 μg/m^3 by the end of the simulation period. This decline demonstrates that large-scale policy interventions can produce substantial and sustained improvements in air quality, although additional efforts are still needed to fully achieve WHO standards.

The Relationship Between Ambient $PM_{2.5}$ Concentration and Electric Vehicle Adoption

In the BAU scenario (Figure 6), the negative relationship between the number of EVs and $PM_{2.5}$ is relatively weak because electric vehicle penetration remains low. This indicates that the small increase in EVs has not been enough to offset the impact of other emission sources.

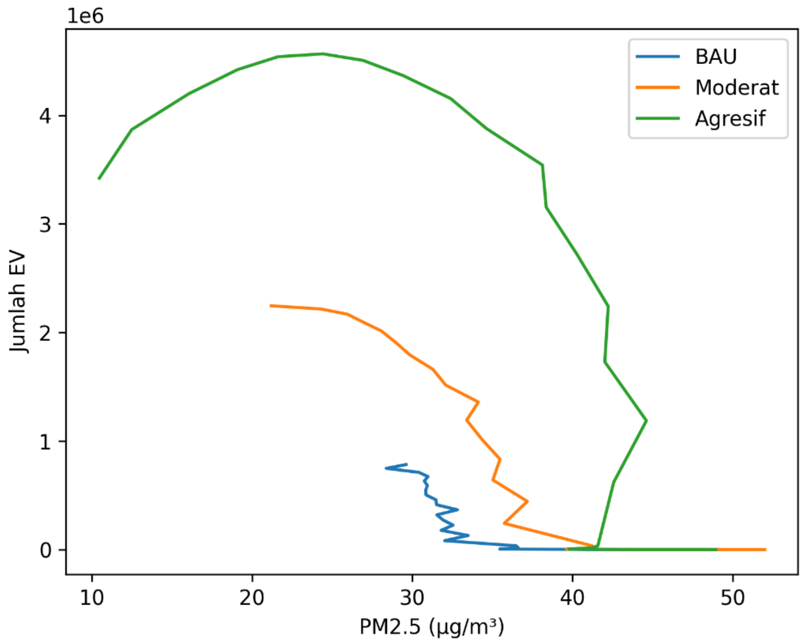

Figure 6. Relationship between ambient $PM_{2.5}$ concentration and the number of electric vehicles

In the Moderate scenario, the relationship between the number of EVs and $PM_{2.5}$ concentrations is very strong, indicating that at intermediate penetration levels, electric vehicles play a major role in controlling transportation emissions. This finding is consistent with the correlation analysis results in the study by Xie (2024), which showed that the impact of EVs on air quality is optimal after passing a certain penetration threshold.

In the Aggressive scenario, the negative relationship remains strong but shows diminishing returns. This indicates that after most vehicles have been electrified, other factors such as residual industrial emissions and meteorological dynamics become the main determinants of $PM_{2.5}$ concentrations. This phenomenon was also reported by Yuan (2021) in their study of large-scale transportation electrification.

Academic Synthesis and Policy Implications

The simulation results indicate that $PM_{2.5}$ control in DKI Jakarta requires an integrated, systems-based policy approach. Electrification of transportation without decarbonization of the energy sector has the potential to result in emission shifts, while an energy transition without conventional vehicle controls would have a limited impact on air quality.

The findings of this study are consistent with international literature emphasizing the importance of integrating transportation and energy policies to achieve significant improvements in urban air quality (Hao et al., 2017). Thus, the developed dynamic system model is not only capable of quantitatively representing $PM_{2.5}$ dynamics but also provides a robust analytical framework to support the formulation of long-term air pollution control policies in dense urban areas such as DKI Jakarta.

CONCLUSION

The developed dynamic system model can quantitatively represent the dynamics of $PM_{2.5}$ emissions and concentrations in DKI Jakarta until 2040. The Aggressive scenario shows the best performance in reducing $PM_{2.5}$ concentrations, while the Business as Usual (BAU) scenario indicates a substantial risk of increasing urban air pollution in the absence of stronger policy intervention. From a policy perspective, the findings suggest that achieving significant $PM_{2.5}$ reduction requires accelerated electrification of the transportation sector, with electric vehicle penetration reaching at least 50% before 2035, accompanied by a renewable energy share exceeding 70% in the electricity mix. In addition, effective air quality control necessitates integrated governance between transportation and energy authorities.

Coordinated planning between regional governments, national energy agencies, and urban transport regulators is essential to prevent emission shifting from the transport sector to fossil-based power generation. This study is limited in that the model applies aggregated emission factors and simplified atmospheric dispersion assumptions, which may not fully capture micro-scale spatial variability and short-term meteorological fluctuations. Future research is recommended to incorporate spatially explicit modeling approaches, such as GIS-based dispersion analysis, as well as real-time air quality monitoring data to enhance model resolution.

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AUTHOR CONTRIBUTION STATEMENT

Chairil Linggabinangkit contributed to the conceptualization of the study, development of the system dynamics model, data collection, model calibration, simulation analysis, and interpretation of the results. Chairil Linggabinangkit also prepared the original draft of the manuscript and performed revisions based on critical feedback. Joni Hermana contributed to the research supervision, methodological guidance, validation of the modeling framework, and critical review of the manuscript to enhance its scientific rigor and policy.

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