Sensitivity of Transformer-Based $PM_{2.5}$ Forecasting to Input Sequence Length

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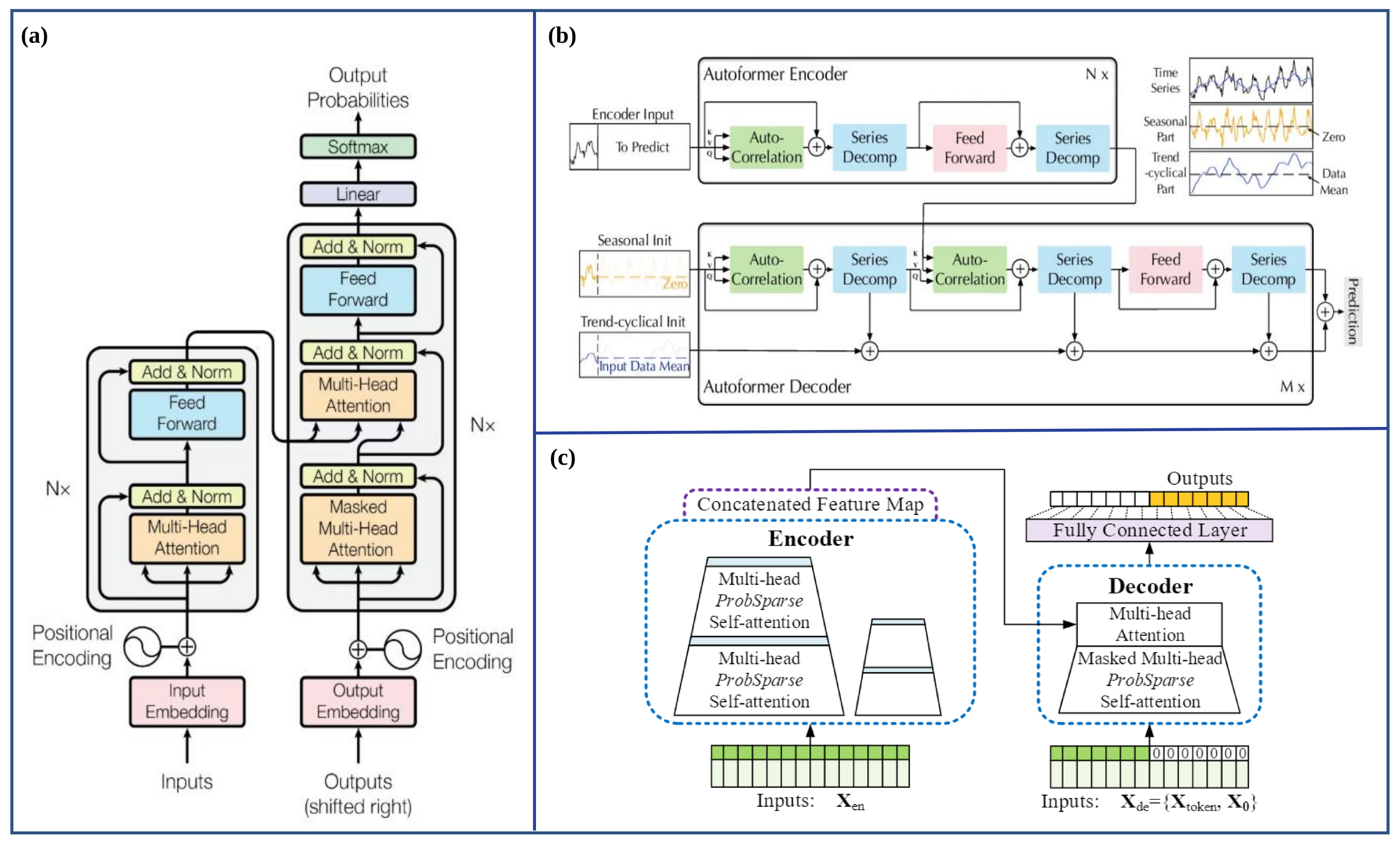
Introduction

- ❖ Accurate $PM_{2.5}$ prediction is essential for air quality management and high-concentration event mitigation, particularly in Seoul where high emissions, complex urban structure, seasonal meteorology, and long-range transport increase prediction uncertainty.
- ❖ Transformer-based models are widely used for air pollution forecasting; however, the effect of input sequence length has not been sufficiently investigated.
- ❖ In this study, three Transformer architectures—Vanilla Transformer, Autoformer, and Informer—were compared under identical conditions, and the impact of input sequence length (72h, 168h, 360h) on short-term (24h) and long-term (72h) $PM_{2.5}$ prediction performance was analyzed.

Model Overview



< Fig 1. Architecture of three Transformer-based models used in this study:
(a) Vanilla Transformer (Vaswani et al., 2017), (b) Autoformer (Wu et al., 2021), (c) Informer (Zhou et al., 2021)>

(a) Vanilla Transformer - VT (Vaswani et al., 2017)

- Uses the full self-attention mechanism to learn dependencies across all time steps.
- Computational complexity grows quadratically with input length, i.e., $O(L^2)$.
- Used as the baseline model in this study.

(b) Autoformer - AF (Wu et al., 2021)

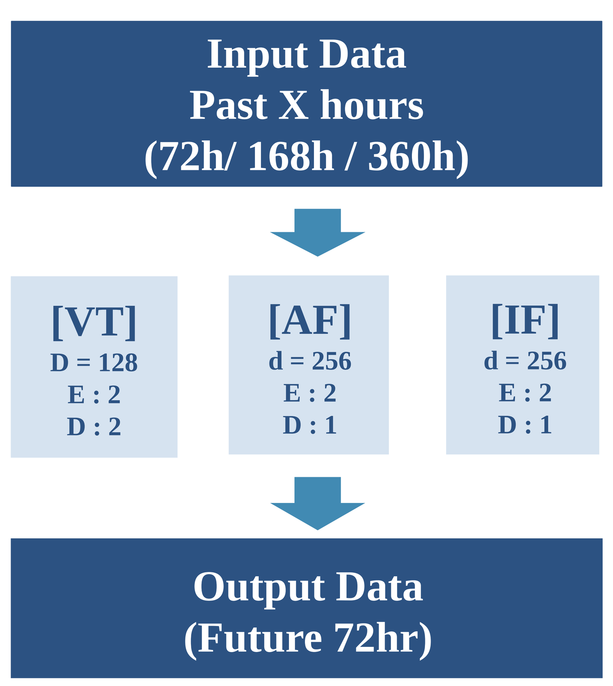
- Replaces conventional attention with Auto-Correlation and decomposes the time series into trend and seasonal components, enabling effective learning of long-term patterns.

(c) Informer - IF (Zhou et al., 2021)

- Employs ProbSparse Self-Attention to reduce complexity to $O(L \log L)$.
- Compresses the encoder sequence through a Distilling operation.
- Designed for long-sequence forecasting.

→ Applying identical input lengths allows the effects of model structure and input length to be analyzed separately.

Methodology



<Fig 2. Workflow Diagram>

- Three Transformer models (VT, Autoformer, Informer) were evaluated under three input sequence lengths (3-day, 7-day, 15-day) and two forecast horizons (24h, 72h).
- Each model's architecture was hyperparameters were individually optimized through tuning.
- All other settings (training data, preprocessing and learning strategy) were fixed identically to isolate the effect of input sequence length.

Study Area & Data

- 25 monitoring stations in Seoul
- 2018 - 2024 Hourly time series data
- Train : 2018 - 2022
- Validation : 2023
- Test : 2024

<Table 1. Hyperparameter settings used in model training>

	VT	Autoformer	Informer
D_model	128	256	256
N_heads	8	4	4
Encoder	2	2	2
Decoder	2	1	1
D_ff	256	512	512
Dropout	0.3	0.3	0.3
Batch size	32	64	32
Learning Rate	1e-5	1e-5	1e-5

<Table 2. Types of input arguments used>

Meteorological Factors		
Temperature	Precipitation	Wind Speed
Wind Direction	Relative Humidity	Atmospheric Pressure
Air Quality Data		
NO_2, SO_2, O_3, CO, $PM_{2.5}$, PM_{10}		
Temporal Encoding		
Hour(sin/cos), Day of week(sin/cos), Day of Year(sin/cos)		

Settings

- Scaling : Min-Max
- Missing : Precipitation → 0 mm / Others → MICE
- Optimizer : Adam
- Loss : MSE Loss
- Early Stopping : Yes(max 1000 epoch)

<Table 3. Actual Epochs (Early Stopping)>

	3-day	7-day	15-day
VT	48	18	51
Autoformer	39	36	38
Informer	40	35	55

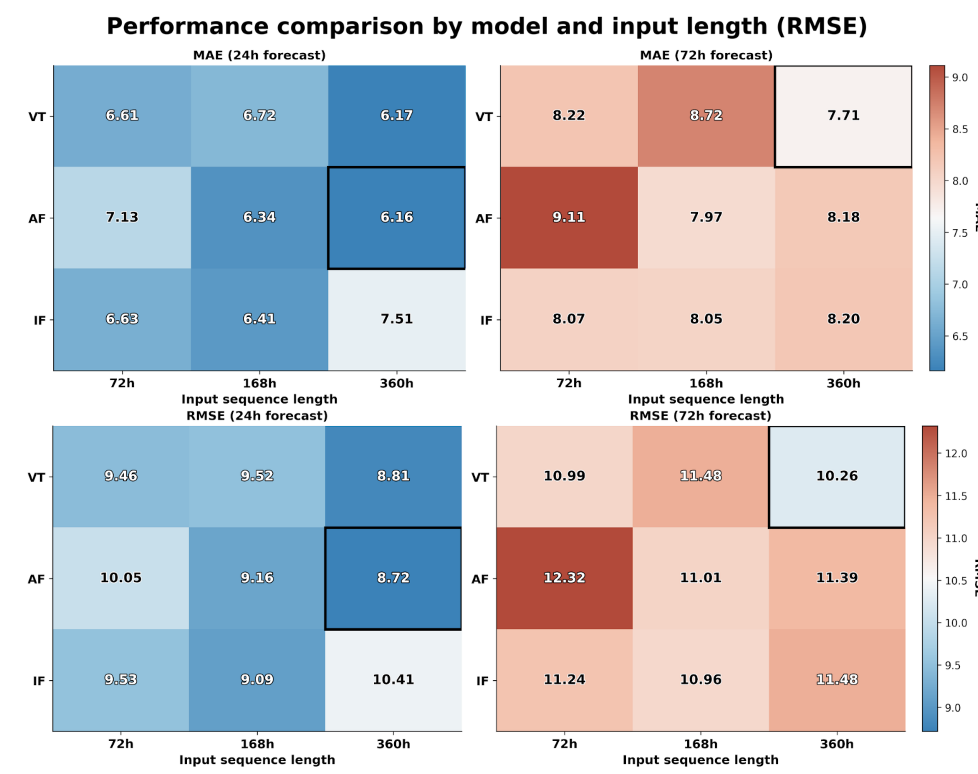
Performance Metrics

<Table 4. Description of evaluation metrics for model performance>

MAE	RMSE	R	POD	FAR
Mean Absolute Error	Root mean squared error	Correlation Coefficient	Probability of Detection	False Alarm Rate

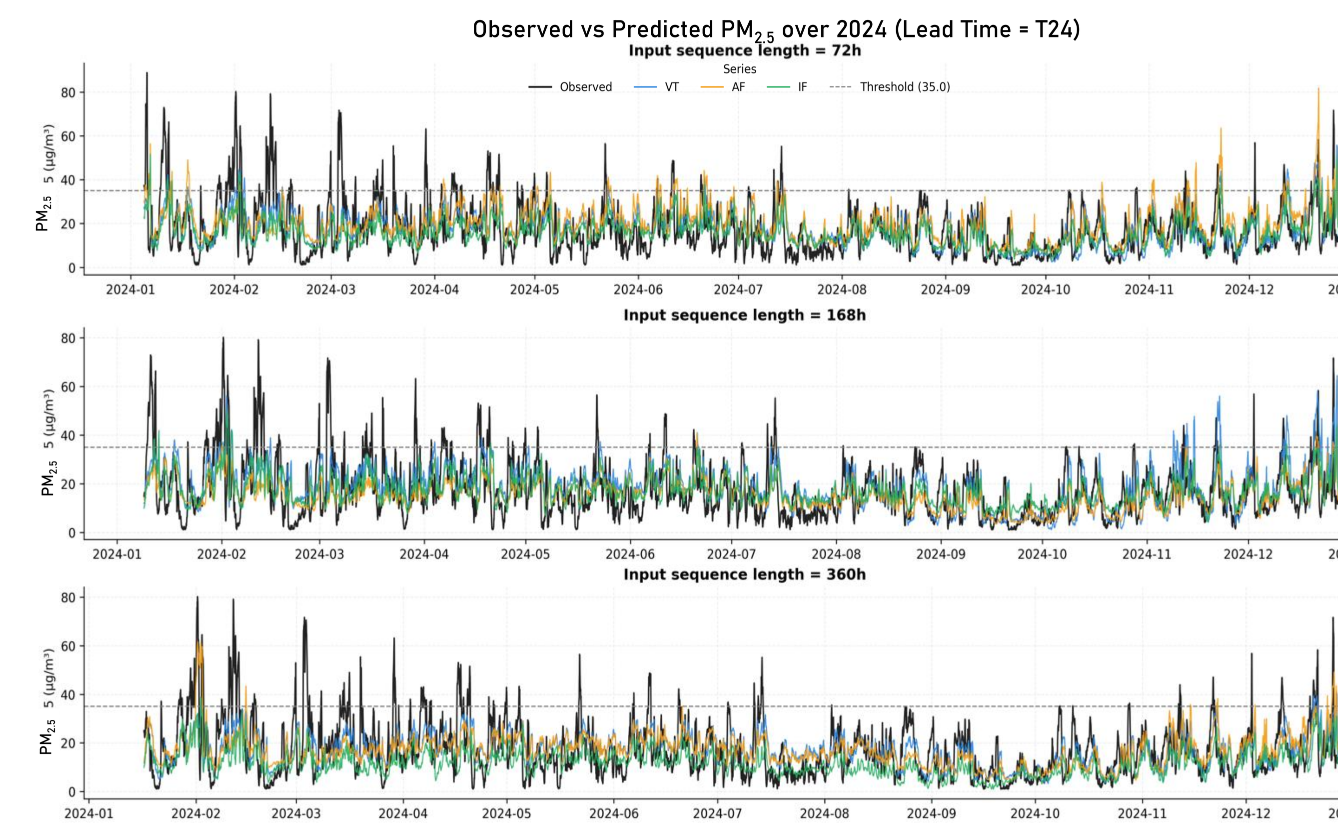
Results

Overall Performance



< Fig 3. Overall Performance>

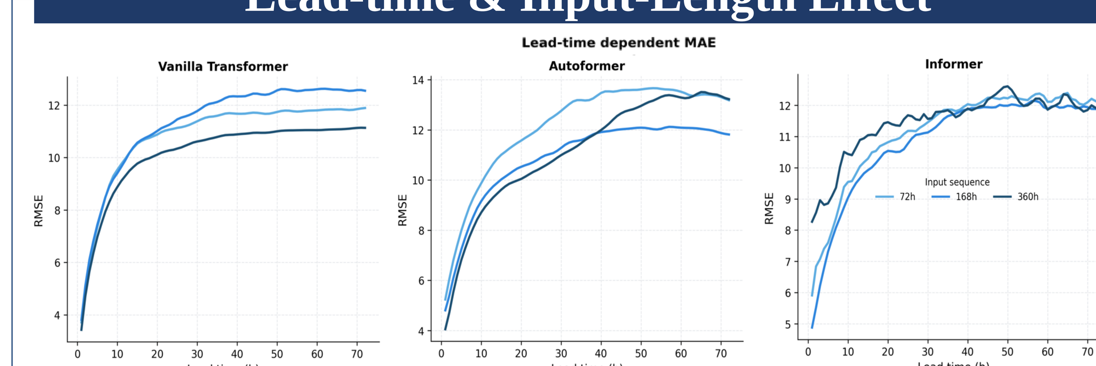
- In the 24-hour forecast, AF-360h achieved the lowest errors (MAE 6.16, RMSE 8.72), followed closely by VT-360h (MAE 6.17, RMSE 8.81).
- In the 72-hour forecast, VT-360h showed the best overall performance (MAE 7.71, RMSE 10.26).
- For both AF and IF, the 168-hour input consistently yielded lower errors than 360h in the 72-hour forecast.
- Notably, the performance gap between 168h and 360h was larger for AF (RMSE difference: 0.38) than for IF (0.52), suggesting that sensitivity to input length varies across model architectures.
- These results indicate that increasing input length does not necessarily improve long-term prediction performance.



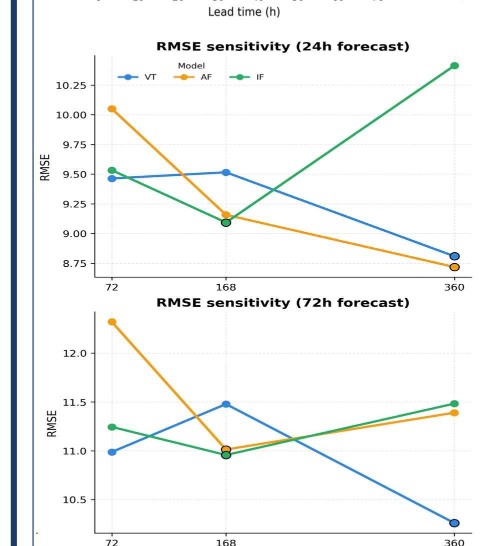
< Fig 4. Annual Time-Series Comparison (T24)>

- All models captured the overall seasonal variability of $PM_{2.5}$ throughout 2024.
- The 360-hour input produced the most stable predictions but tended to underestimate sharp concentration peaks, while the 72-hour input better reproduced peaks but with greater variability.
- This indicates a trade-off between prediction stability and peak reproducibility depending on input length.

Lead-time & Input-Length Effect



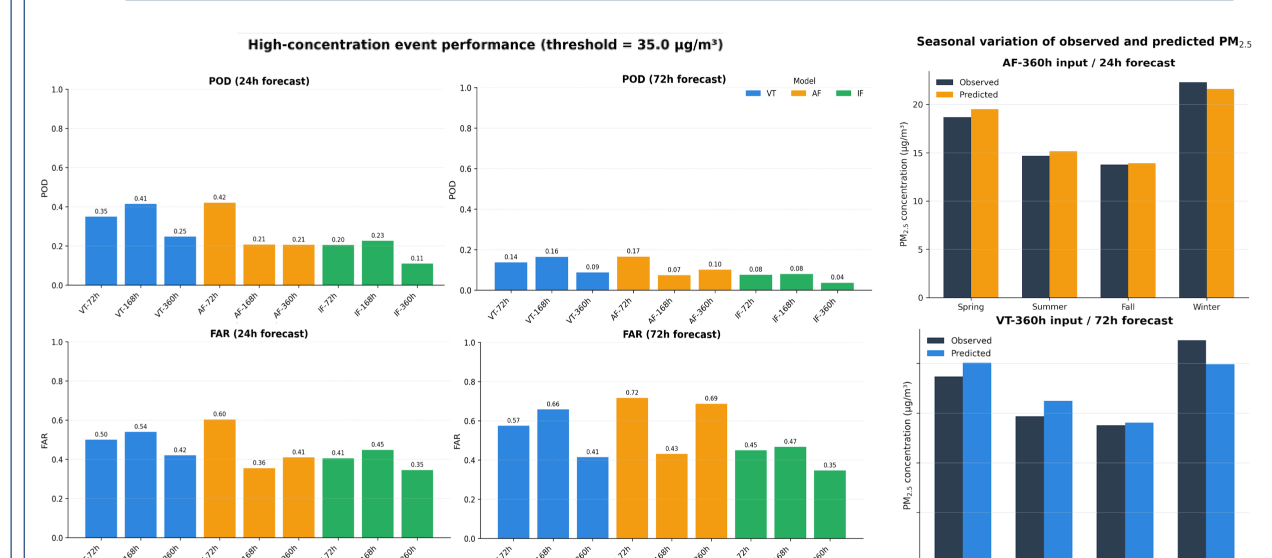
< Fig 5. Lead-Time Effect>



< Fig 6. Input-Length Sensitivity>

- Errors increased with longer lead times, but the effect of input length varied by model.
- VT: Best performance at 360h for both forecasts (24h RMSE: 8.81, 72h: 10.26), with a non-monotonic pattern.
- AF: Improved up to 168h, but 360h improved only 24h forecast (RMSE 8.72) and worsened 72h (RMSE 11.39).
- IF: Optimal at 168h (24h RMSE: 9.09, 72h: 10.96); 360h increased errors for both.

Seasonal & High-Pollution Events



< Fig 7. Seasonal & High-Pollution Events>

- South Korea showed clear seasonal $PM_{2.5}$ patterns, with spring overestimation and winter underestimation.
- A POD–FAR trade-off was observed for high-$PM_{2.5}$ events (≥35 µg/m³).
- AF-72h detected more events but produced more false alarms.
- AF-360h and VT-360h captured seasonal patterns, but winter peaks were underestimated.

Conclusion

- ❖ This study demonstrates that input sequence length is a key factor influencing the performance of Transformer-based $PM_{2.5}$ prediction.
- ❖ For short-term (24h) prediction, AF-360h was the most suitable as it stably captured trend and seasonal patterns.
- ❖ For long-term (72h) prediction, VT-360h showed the best performance by effectively learning global temporal dependencies.
- ❖ Therefore, input sequence length should be selected according to model structure and forecasting objective, not simply "the longer, the better."

Acknowledgements

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