Temporal Kolmogorov-Arnold Networks for Robust Multi-Horizon PM2.5 Forecasting

The global burden of air pollution has increased since 1990, with $PM_{2.5}$-related deaths rising by 700,000 over 25 years [1], and its related health effects have emerged as a major environmental and public health concern over the past decades [2]. $PM_{2.5}$ is one of the most toxic air pollutants, as it penetrates deep into the lungs and can cause chronic diseases or premature death. The impact of meteorological factors, industrial emissions, and urbanization has made $PM_{2.5}$ forecasting more and more difficult. Despite the progress of statistical approaches (ARIMA, SARIMA), machine learning methods (XGBoost, Random Forest, SVMs), and deep learning techniques (RNNs, LSTMs, CNNs, Transformers), they struggle with long-term predictions and perform poorly with sparse or low-quality data, common in Africa. Thus, this makes $PM_{2.5}$ forecasting particularly challenging on the continent.

To address this, we propose the use of **Temporal Kolmogorov-Arnold Network (TKAN)**, a deep learning model particularly suitable for scenarios involving sparse or low-quality data. TKAN leverages spline-based functional representations to improve robustness across short (1–3 days ahead) and long-term (9–12 days ahead) forecasts. Our dataset includes daily maximum meteorological and air quality variables from 8 African countries and 15 cities. The preprocessing steps included imputation with column means, rolling median scaling (14-day window), RobustScaler transformation, and sequence preparation with n_{ahead} forecasting.

We compared TKAN with GRU, LSTM, and a hybrid WOA-CNN-LSTM-AM model. Training employed callbacks (early stopping, learning rate reduction on plateau) and Optuna for hyperparameter optimization. Evaluation metrics included MAE, RMSE, LogCosh, Huber loss, and R^2. TKAN achieved the best R^2 scores of 0.5107, 0.4746, 0.4719, and 0.4105 for 1-, 3-, 9-, and 12-day forecasts, respectively, while maintaining lower RMSE values than baselines. Compared to state-of-the-art models [3, 4], TKAN improved R^2 by up to 70.7% and RMSE by 16.5% for long-term horizons, demonstrating stability and superior generalization for African air quality forecasting.

Table 1: Comparison of $PM_{2.5}$ prediction metrics across models **(left)** and with SOTA methods **(right)**, for 1, 3, 9, and 12-day horizons on the test set (20% of the dataset). Best values in **bold** (lower is better except for $\boldsymbol{R^2}$).

Period	Model	MAE↓	RMSE↓	LogCosh↓	Huber↓	R^2↑
1-day	GRU	0.0650	0.1949	0.0173	**0.0170**	0.4923
	LSTM	0.0754	0.2063	0.0197	0.0213	0.4312
	TKAN	**0.0647**	**0.1913**	**0.0171**	0.0183	**0.5107**
3-day	GRU	0.0840	0.2078	0.0199	0.0216	0.4233
	LSTM	0.0797	0.2050	0.0194	0.0210	0.4386
	TKAN	**0.0674**	**0.1983**	**0.0183**	**0.0197**	**0.4746**
9-day	GRU	0.0988	0.2260	0.0231	0.0255	0.3210
	LSTM	0.0782	0.2041	0.0193	0.0208	0.4458
	TKAN	**0.0716**	**0.1993**	**0.0184**	**0.0198**	**0.4719**
12-day	GRU	0.1221	0.2591	0.0298	0.0333	0.1079
	LSTM	0.0783	0.2278	0.0235	0.0259	0.3108
	TKAN	**0.0736**	**0.2106**	**0.0204**	**0.0222**	**0.4105**

Period	Model	MAE↓	RMSE↓	LogCosh↓	Huber↓	R^2↑
1-day	[3]	0.0776	0.2437	0.0267	0.0297	0.2061
	[4]	**0.0600**	0.2026	0.0183	0.0205	0.4512
	Our solution	0.0647	**0.1913**	**0.0171**	**0.0183**	**0.5107**
3-day	[3]	0.1004	0.2333	0.0248	0.0272	0.2729
	[4]	0.0704	0.2269	0.0231	0.0257	0.3122
	Our solution	**0.0674**	**0.1983**	**0.0183**	**0.0197**	**0.4746**
9-day	[3]	0.0882	0.2467	0.0273	0.0304	0.1902
	[4]	**0.0703**	0.2179	0.0214	0.0237	0.3680
	Our solution	0.0716	**0.1993**	**0.0184**	**0.0198**	**0.4719**
12-day	[3]	0.0807	0.2522	0.0283	0.0318	0.1552
	[4]	0.0836	0.2573	0.0294	0.0331	0.1202
	Our solution	**0.0736**	**0.2106**	**0.0204**	**0.0222**	**0.4105**

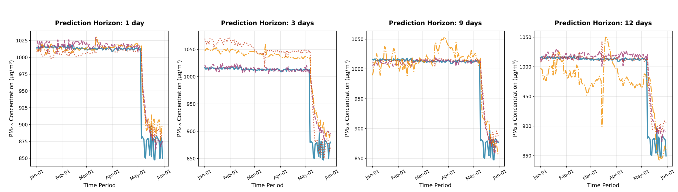

Figure 1: Comparison of predicted and ground truth $PM_{2.5}$ values across multiple horizons ($n\_ahead = 1, 3, 9, 12$). Results show a representative 6-month period from the test set, comparing the predictions of TKAN, GRU, and LSTM models against ground truth values.

References

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