Modelling and Real-time Optimisation of Air Quality Predictions for Australia through Artificial Intelligence Algorithm

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INTRODUCTION

Air pollution causes more than 3000 premature deaths. Annually, this health issue cost Australians $24.3 billion in public health expenses[1]. This calls for a prompt action to have an efficient air quality regulating mechanism. Particle pollution is a major air quality issue[2]. Accurate predictive models are important for regulatory plans for the public and different vulnerable groups such as children, pregnant women and the elderly.

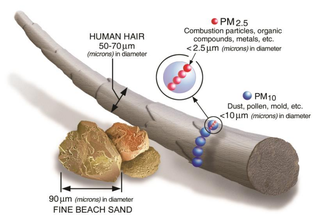

Figure 1: Comparative sizes of airborne pollutants.
Source : Environment Protection Authority

- To model air quality, artificial intelligence can be a promising tool to generate predictions through a novel learning algorithm.
- The project develops intelligent models for real-time air quality forecasting. It will consider air quality indicators: fine Particulate Matter 2.5 ($PM_{2.5}$), coarse Particulate Matter 10 (PM_{10}), and the atmospheric visibility reducing particles.

IMPORTANCE OF KEY STUDY SITES

Queensland (Brisbane, Gladstone & Mackay)

- Highest amount of greenhouse gases.
- Industrial activity and Coal dust emissions.

New South Wales (Sydney & Newcastle)

- Sydney is highly populated with most polluted suburbs.
- Newcastle is world's largest black coal exporting port[3].

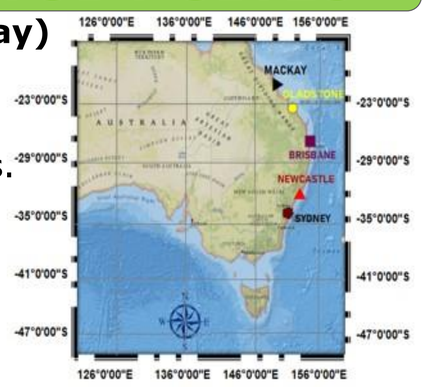

Figure 2: Study region and locations for which artificial intelligence model is designed for hourly air prediction.

ARTIFICIAL INTELLIGENCE ALGORITHM

The project will design an online sequential-extreme learning machines (OS-ELM) as AI algorithm integrated with improved ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) as a data pre-processing system. Model performance is evaluated for statistical accuracy and benchmarked against alternative models such as ICEEMDAN-multiple linear regression (MLR), ICEEMDAN-M5 Tree, OS-ELM, MLR & M5 Tree.

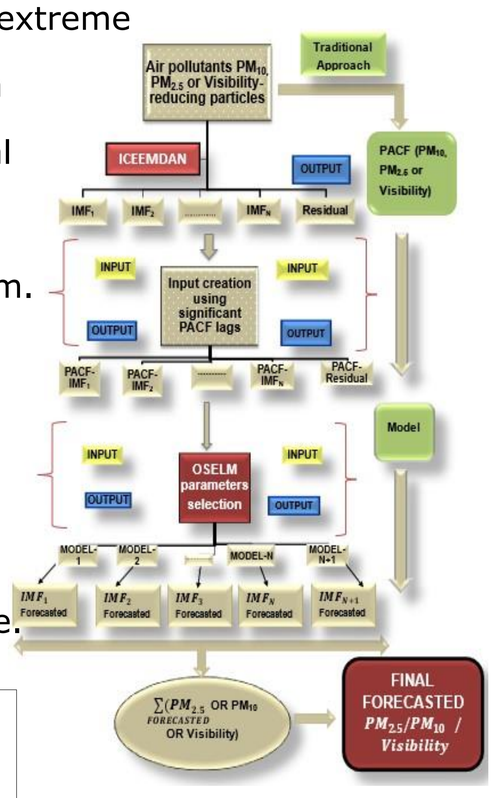

Figure 3: Flowchart and steps of model design for ICEEMDAN-OSELM. Here IMF = Intrinsic mode functions, PACF = partial auto-correlation function, and N = IMF Number.
The model designations are: MLR (Multiple Linear Regression) and M5 Tree (a kind of decision tree).

PROJECT RESULTS

The proposed novel learning algorithm (ICEEMDAN- OSELM) outperform other models. It has a high correlation coefficient between observed and predicted air quality and low root mean square error.

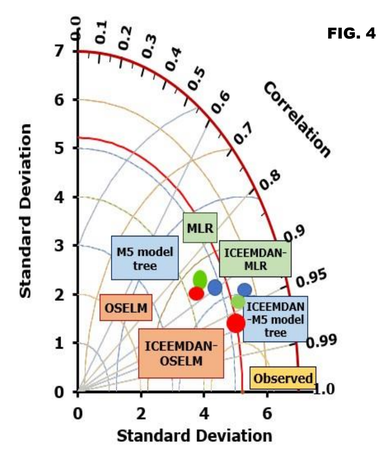

Figure 4: Taylor Diagram illustrating model preciseness in terms of RMS centred difference confirmed the versatility of the ICEEMDAN-OS-ELM *vs.* the comparative models.

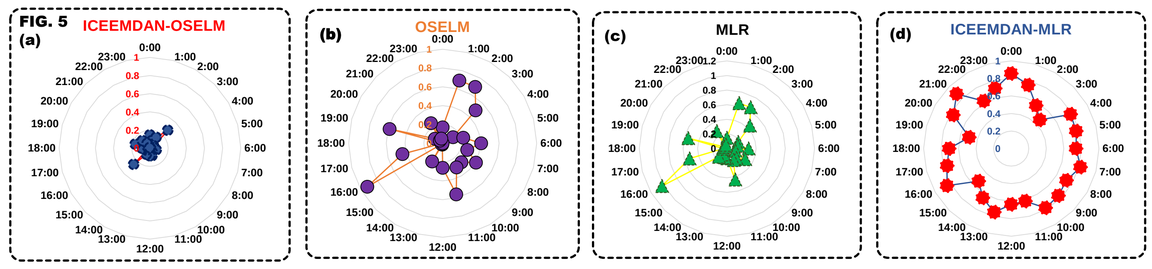

Figure 5(a-d): Relative forecast error (%) generated by ICEEMDAN-OS-ELM *vs.* comparative models for Brisbane ($PM_{2.5}$). Radial axis outward denotes magnitude per hour. ICEEMDAN-OSELM generates lowest error.

CONCLUSION

The project comprehensively considers synergistic effects of atmospheric variables in predicting air quality through artificial intelligence. This robust predictive framework is useful as a decision support system for real-time air quality monitoring. Artificial intelligence models can help save money and resources for health sector, and significantly reduce Australia's public health risk burden.

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