Development of Real Time Meteorological Grade Monitoring Stations with AI Analytics

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***Abstract*—Air pollution comes in many forms and the basis of measure is the concentration of particles in the air. The quality of air depends on the quantity of pollution measured by a particle sensor that is accurate down to micron-meter consistencies. The size of the pollutants will be ingested by humans and cause respiratory problems and its effects on health conditions. The research will study the measurement of particles using multiple types of light scattering sensors and reference them to the accuracy of meteorological standards for precision in measurement. The sensors will be subjected to extreme conditions to gauge the repeatability and behavior and also long-term deployment usage. This study is required as when deployed on the field, dust particles will degrade the sensors over time. Early detection of sensor sensitivity and maintenance is therefore considered part of the research. Air particle data is volatile and dynamic over time and with that said, mass deployment of these sensors will give a better measurement of pollution data. However, with more and more data, standard statistics used show a basic level indicator and hence the idea of using machine learning algorithms as part of artificial intelligence (AI) processing is adapted for analyzing and also predicting particle data. There is a foreseeable challenge on this as there is no one machine learning for use only for this and multiple models are considered and gauged with the best accuracy using R2 value as low as 0.75 during the entire research. Lastly, with the seamless Internet of Things sensing architecture, the improved spatial data resolution will be improved and can be used to complement the current pollution measurement data for Malaysia in particular.**

Keywords*—*Air pollution; air particles; PM2.5; PM10; real time; light scattering sensor; neural networks; AI; machine learning; R2; IoT; WSM

I. Introduction

Pollutants in the air are not clearly visible and they come from many different sources. Air pollution is a mix of particles and gases that can reach harmful concentrations both outdoors and indoors [1]. Its effects range from disease risks such as respiratory to cardiovascular symptoms [2]. Smoke, mold, pollen, methane, and carbon dioxide are just a few examples of common pollutants that can affect the air surroundings [3].

The measurement of air pollution is measured in PM2.5 and PM10. PM refers to particulate matter which means particles in the air. The number 2.5 and 10 is the measurement in microns [4]. Particles the size of 2.5 microns and below are considered harmful as they could enter the blood stream and do damages years before any side effects occurs [5].

A limited number of meteorological stations in Peninsular Malaysia nationwide as shown in Fig. 1 gives a basic level of the air quality readings in the country (https://apims.doe.gov.my/). Systems in place are also located mostly in open areas far from densely populated places such as schools and factories. Data gathered are recorded, processed and shown but there are no algorithms for any preventive methods or predictive approach that could be performed. Only when pollution occurs, the data will be of interest to be monitored [6].

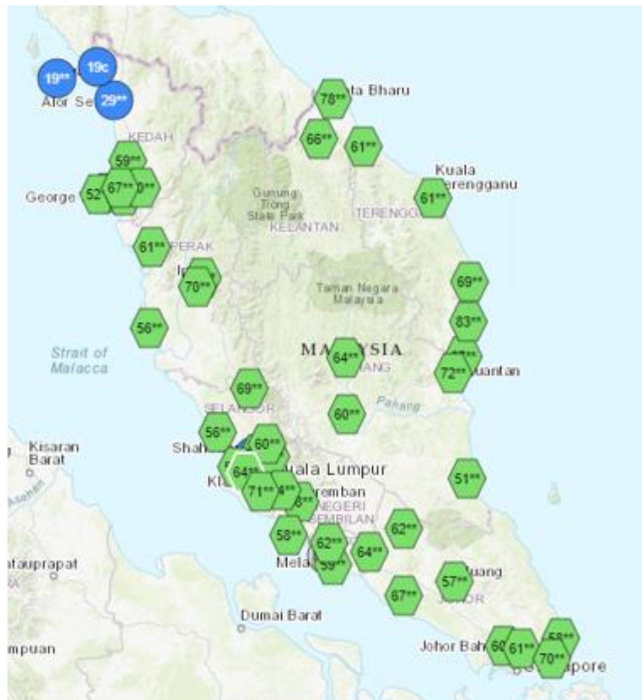

Fig. 1. Installation of meteorological stations in Malaysia.

The presented research focusses on market available particle sensors from various suppliers and the study of correlation of each sensor selection is benchmarked for its performance with the same environment and setup scenarios. The selection of particle sensor used will then be subjected to the meteorological reference to study its difference and an option to apply filtering mechanism for sensor data accuracy and traceability. Interface of the sensors and publishing the data to the cloud will be heart of the hardware being develop [7]. The hardware development will be in a form of an Internet of Things (IoT) node which is portable, energy efficient and ease of deployment and will be connected to the mobile network [8]. Altogether the hardware system will enable ease of deployment for mass monitoring and thus more perimeter of areas will be covered with real time data on concentration of the air pollutions [9]. As more systems deployed, the sensor data generated will be used for ingestion into the machine learning models for advanced processing on the prediction of the particulate matter. Machine learning models will be programed as a custom mode for particle data usage and models will be used based evaluated on based on the outcome of prediction accuracies and errors. In concluding the research presented, the IoT node will be able to measure particle sensor values accurately as of with meteorological standards with real time access and the overall system will be able to alert and provide predictive results based on artificial intelligence algorithms adapted that work behind the scenes [10].

Current and previous case studies and papers on air quality are based on meteorological sensors and as for Malaysia, there are not enough stations for monitoring dynamic conditions on the pollution that is causing the haze pollution. Therefore, additional stations whether it is meteorological or other particle sensor types are required. Cost-effective particle sensors that are used in some of the research are also not correlated to the meteorological side, hence it gives a sense of ambiguity on the results presented [11]. This research therefore would contribute and bridge the gap on these limitations using particle sensors that are based on the accuracy of the known standard with multiple deployment of sensors to complement the measurement data. Moreover, the systems designed and presented here are locally assembled.

The state of system design will be presented in the following chapters which include the study of sensors, the design of IoT and the correlation of the data with the Department of Environment (Malaysia) [12]. The backend of the systems utilizes the node and server architecture with web dashboard for first-hand information of IoT status. Machine learning models are then presented with comparative analysis against with R2 values as a scoring index on how well the models perform.

II. Methodology

A. Particle Sensor Selection and References

Particle measurement is related to the number of particles in an area at a point in time. These particles are extremely small; thus, it needs an accurate and precise sensor to be able to measure the particle sizes. The principle of particle measurement using a laser beam with particles blown over a detector and the reflection of the dust over time is counted and correlated with particle sizes and densities of the internal formulation of the sensor [13].

Three selections of particle sensors are considered from different manufacturers such as Honeywell, Sensirion and from China and shown in Fig. 2 [14]. The sensors are commonly used in industries and the reason of early selection. All three sensors are placed side by side and data is collected over a period of 45 days. This gives an equal level baseline on the particle data captured amongst the sensors being studied. The airflow, height, and simulated pollution levels are then conducted and data collected and compared. The co-relation of measured data is observed with an interval or 10 minutes and shown in Fig. 3 [15]. The hardware controlling the sensors were built to accommodate the three different sensors protocol and data is stored on the local storage. The dynamic range of all sensors are identical with co-relation of more than 90%. All three sensors are seen having the same identical behaviors. The resulting three sensors are equally suitable for deployment and the one being chosen to be used for this research is brand CN which comes with a protective outdoor casing. This sensor is chosen also due to the availability of the calibration certification ensuing the sensor is conformed to the specifications specified.

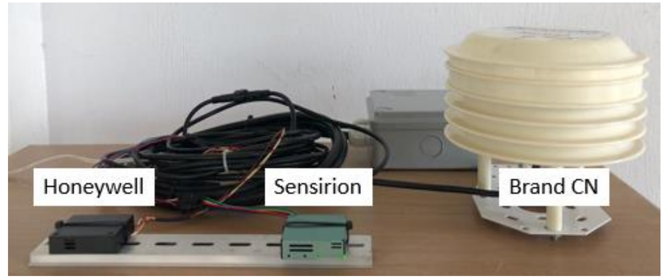

Fig. 2. Particle sensor selection and validation.

The brand CN sensor was then installed on the Department of Environment (DOE) in the Klang Valley meteorological station. There are two sets of the same sensors being placed for the study and comparison of the data repeatability alongside the reference standard. Data from the DOE particle sensor is then compared with the result of capture. Upon analysis, there are noticeable spikes in some of the range of the readings compared with the meteorological and the sensor used for the research. These spikes were due to the sensitivity and dynamic range of the sensors being used compared to the reference standard. Nevertheless, the trend of all the sensors is showing to be of identical trace.

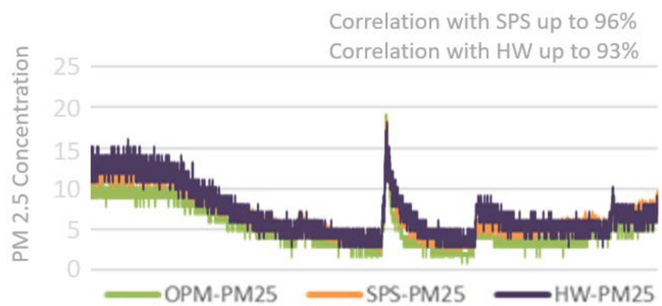

Fig. 3. Particle sensor correlation values and trend.

A study to improve the correlation of the sensor versus the DOE reference was embarked and Kalman filtering technique was adapted due to its usage for in noisy and dynamic sensors such as gyroscope sensors to normalize to the targeted reference [16]. The data that were captured were then passed to the Kalman algorithm to validate the outcome. The Kalman filtering consists of two main steps which are the prediction step and the update step with the following formula in Eq. (1).

$$x\hat{}k \mid k-1 = Fkx\hat{}k-1+Bkuk \quad (1)$$

where, x^k ∣ k−1 is the predicted state estimate in time k and Fk is the state transition matrix which describes the dynamics of the system, x^k is the previous state estimate, Bk is the control input matrix and uk is the control input at time k.

The Kalman filter estimates the system's states by predicting its next state using previous estimates and systems dynamics and minimizes the estimation error iteratively in turn makes the particle sensor referenced and improving its states to the known meteorological grade standard. The implementation of Kalman filter in the data processing of particles measurement data is shown in Fig. 4.

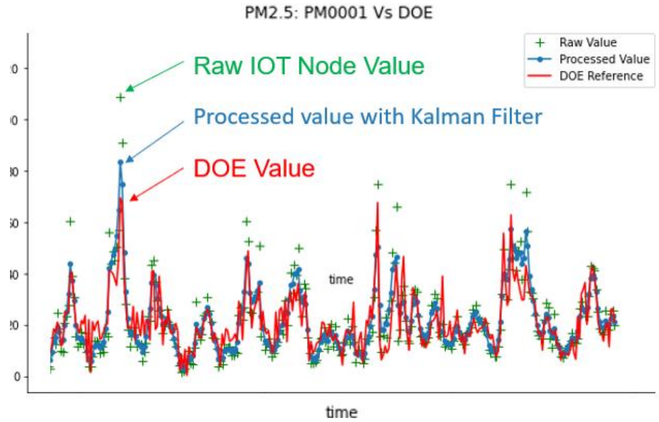

Fig. 4. Data processing using Kalman filtering algorithm.

B. Design of Wireless System Network (WSN) Hardware

Standalone API monitoring sensors form the basis of Wireless System Network (WSN) [17]. The development and requirement of the IoT hardware were carefully architected and specifications were designed to be adaptable and expandable to other types of sensors and connectivity. Other features such as low power usage <1Watts (idle) which is ideal for battery and solar power for off-the-grid deployment [18]. Splash-proof IP rating casings and connectors are also put in place for outdoor usage. The wireless communication used for the IoT nodes is Wi-Fi and option for 4G LTE mobile GSM networks for remote monitoring in rural areas. The communication protocols used were HTTP [19].

There are three iterations of prototypes of the IoT systems being designed and system validation and verification were carried out to finalize the first proper design of the deployment hardware [20]. Some problem that requires improvement such as RS485 protection circuitry were added as the IoT is likely to be damaged due to AC spikes and also lighting surges due to the system being placed open air in the field. Other improvements such as using a DC-DC converter for efficient power delivery versus a linear regulator were improved. This was crucial and required to be done as there are up to thirty-six systems that we build and to be deployed. The systems need to be robust and free of any maintenance or minimal problems on site. Fig. 5 showcases the hardware prototype being tested with the sensor connected to the 4G network while communicating with the server side. The hardware is then constructed and designed onto a PCB for final deployment with the proper housing and mounting in a pole with sensors altogether in one.

The IoT system generates several data from the sensors such as PM2.5, PM10, temperature, humidity, wind speed, direction and GPS location [21]. These sets of data are then pushed to the cloud server network for statistical data generation to build a web-based dashboard [22]. The interval of data transferred is set by default to be 30 seconds and can be triggered on demand as well for comprehensive monitoring if required. All the communication through and from the server is encrypted and error error-checking mechanism is used to ensure data transfer is successful and not corrupted. In the IoT system, there are various internal functions that are running in parallel, therefore the firmware that is built requires the system to be efficient and tasked deterministic and therefore a real time operating system is adapted with the structure is shown in Fig. 6. The structure itself is a simplified state machine architecture and this is the basic building block of the IoT system being built upon.

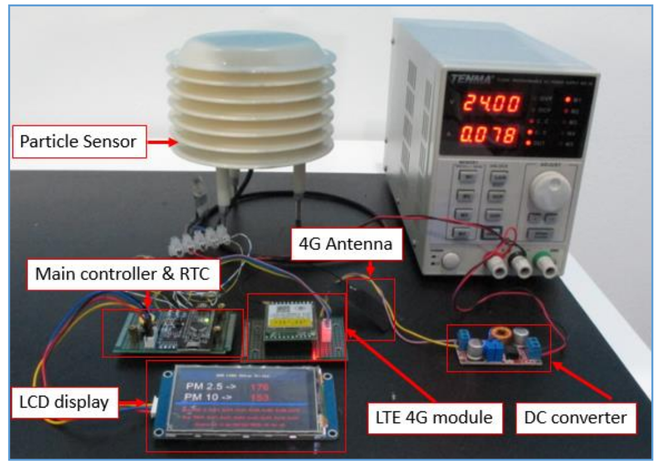

Fig. 5. Prototype IoT module.

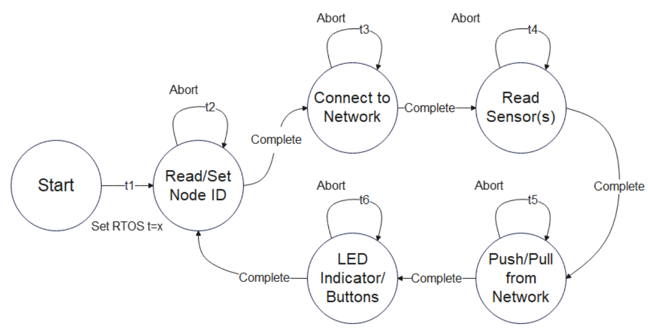

Fig. 6. Real-time operating system structure.

C. Data Processing

When the data is pushed to the cloud, a backend server-client dashboard is built in place to showcase the data based on time and day, and also a classification of API readings according to the standards on the IoT Nodes. This dashboard also serves as an indicator of the status of the connected sensor hardware that was deployed and activated on the field. This enables ease of measurement and also data storage from the sensor networks [23]. Basic analytical information based on mathematical statistic formulas is computed such as high, low, mean values of sensor data [24]. The client-side dashboard is shown in Fig. 7 which shows the real-time status of the connected IoT nodes along with the sensor measurement results.

Upon collecting and analyzing the measurements, the historical data will be used to serve as a base for AI modelling and processing. The AI algorithm will be used for predicting pollution ahead of time [25]. There are up to four types of machine learning models used and compared. They are the linear regression [26], ARIMA, Neural Prophet and the LSTM [27]. There are pros and cons in each algorithm being used and the basis of the modelling is time series type which is suited to the particle data being measured. Multiple machine learning models were studied and compared also as there the outcome of the prediction is different based on how the input dimensions and data types are being ingested and computed internally [28].

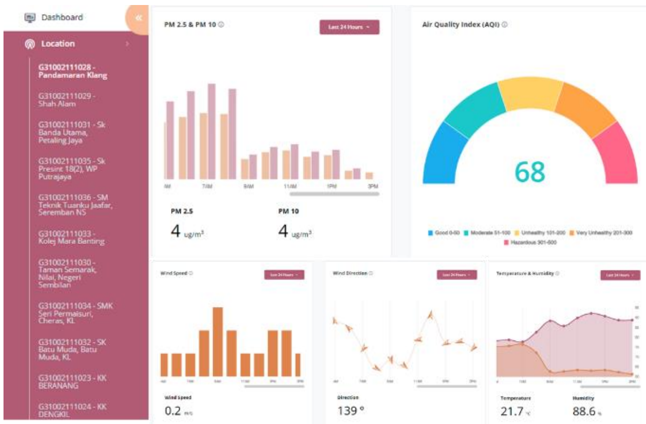

Fig. 7. Web dashboard view on data from sensors.

III. Results

The overall research results focus on the machine learning computation outcome. The AI modelling uses the 80% training and 20% test case data and all the four models are fed with the same data period for comparison of outcome [29]. The data range used is a year collection of historical data which is from 15th March 2022 to 15th March 2023 on a particular IoT station (KK Nilai). The data that were ingested is from the particle measurement (PM2.5) sensor along with the time series points. There summary of outcome for the algorithm used is shown in Table I.

TABLE I. Comparison of AI Performance Index on Algorithm Used

	Linear Regression	ARIMA	Neural Prophet	LSTM
MAE	18.84	18.51	7.34	7.35
RMSE	22.43	22.00	10.26	9.72
R2	0.26	0.22	0.49	0.75

From the observation on the machine learning models used, it could be concluded that the statistical algorithm types are less accurate in prediction with the R2 value of below ⩽0.26. The Neural network types are suitable for prediction on this particle measurement (PM2.5) data and in the research presented as the R2 score is up to 0.75 with the LSTM method [30]. For pictorial visualization, the Fig. 8, Fig. 9, Fig. 10 and Fig. 11 shows a clear distinction on the statistical algorithm compared to neural types [31]. The prediction of the test data does not really contain any patterns and it could be said as of flat computation. On the other hand, for the neural network types, the prediction pattern can be seen and matching the flow of the test data [32].

Based on overall data and results, neural algorithm method can be seen as performing better as they are inspired by the structure and functioning of the human brain. It is a key component of machine learning, specifically a subset known as deep learning. Furthermore, neural networks are used for tasks such as pattern recognition, classification, regression, and more, by learning from data.

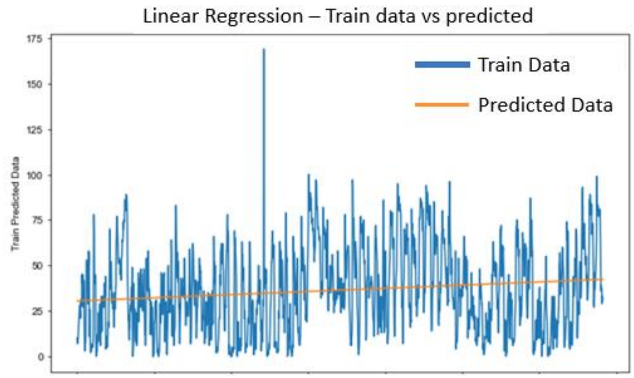

Fig. 8. Linear regression modelling.

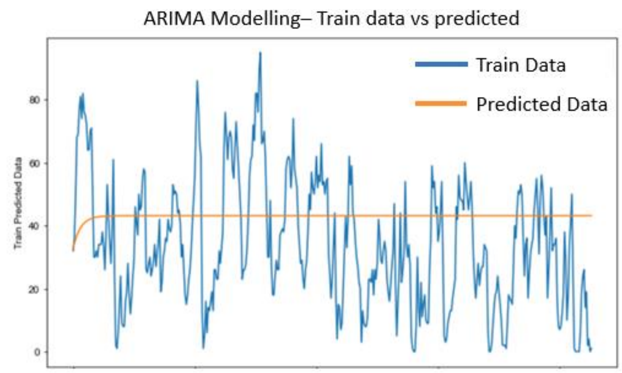

Fig. 9. ARIMA modelling.

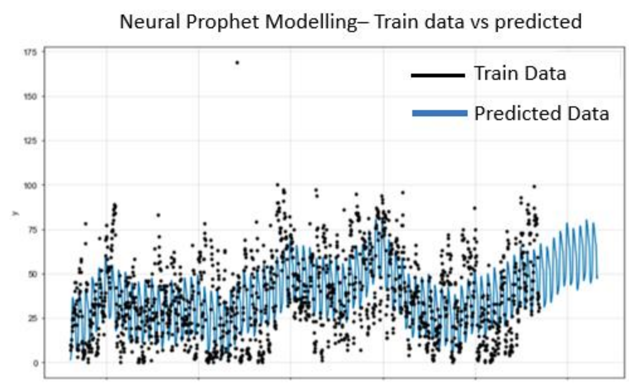

Fig. 10. Neural prophet modelling.

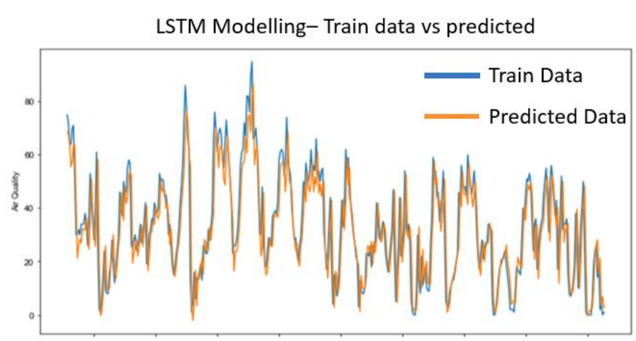

Fig. 11. LSTM modelling.

The LSTM model perform better is also due to the multi epoch used together with seasonality computation for ingestion while the rest uses the basis of time series modelling or single dimensional data for ingestion [33].

IV. Discussion

The successful integration of sensor selection, hardware design, and server-side processing has resulted in a comprehensive air quality monitoring system designed into an IoT based system. The deployment of this system on-site has demonstrated its capability to provide accurate, real-time air quality data, which is essential for informing public health strategies and environmental policies. Measurement of particle data is compared with DOE first hand to gauge the correlation and reproducibility of the measured air quality data [34]. Server based web API displays the IoT stations status with real-time on demand access using 4G GSM network. Future enhancements will focus on expanding the network of monitoring units and incorporating additional data sources to further improve prediction accuracy and system robustness.

There are two known limitations for the research which is on the long-term accuracy and maintenance of the sensors being used for the particle measurement. The Department of Environment (DOE) sensors are maintained regularly and calibrated to a traceable standard [35]. However, this sensitivity or performance of the sensor can be monitored using a machine learning algorithm using abnormal detection.

The second limitation is on the data processing with artificial intelligence algorithms. As the known research uses the data from meteorological sensors, there are years of historical data readily to be used and ingested into the algorithm [36]. The historical data from meteorological sensors contains additional sensor data such as pollution gases which is an advantage when using multivariate [37] AI modelling which serves as a multiple-dimensional processing and greatly influences the prediction outputs [38] [39].

V. Conclusion

From the sensor IoT node deployment to data generation and retrieval, this research presents the sensors being used is able to perform with high standards of measurement by referencing to a known standard. The IoT system hardware itself plays the main part in where sensors are being interconnected and data is fed back to the cloud for processing and storage. A step further in processing the data using AI algorithms is experimented and classification of the trend of data with anomalies seen of the data being produced and rectified with normalization [40]. The demonstrated predicted results using machine algorithm with an RMSE of 9.72 for LSTM is suitable for forecasting and detection of pollution levels ahead in time [41]. Hence, this information could be fed to other broadcast networks for notification. Lastly the presented system is not constrained to air pollution only and can be easily adapted to other types of pollution that compromise quality of life in urban areas, e.g. noise pollution, hazardous gases and more [42].

Acknowledgment

The author wishes to extend his profound gratitude to the Department of Environment Malaysia (DOE) on permission for installing the IoT sensors and data shared during the research. This work was partly financed by iRadar Sdn. Bhd. on hardware, engineer access and countless arrangements for deployment and setup on sites.

References

[1] MacNee, W. and Donaldson, K. (2003). Mechanism of lung injury caused by PM10 and ultrafine particles with special reference to COPD. European Respiratory Journal 21(40): 47s-51s.

[2] Khan S, Sahu V, Kumar N, Gurjar B. Particulate matters deposition in the human respiratory system: A health risk assessment at a technical university. JAPH. 2024;9(1):1-14.

[3] Ranathunga N, Perera P, Nandasena S, Sathiakumar N, Kasturiratne A, Wickremasinghe R. (2019). Effect of household air pollution due to solid fuel combustion on childhood respiratory diseases in a semi urban population in Sri Lanka. BMC Pediatr. 2019;19(1):306.

[4] Brunekreef, B. and Holgate, S. T. (2002). Air pollution and health. The lancet 360 (9341): 1233-1242.

[5] Zheng, Yijing, Ooi, Maggie C. G., Juneng, Liew, Wee, Hin B., Latif, M. Talib., M. Nadzir, M. Shahrul, Hanif, Norfazrin, Chan, Andy, Li, Li, Ahmad, Norfazilah, Tangang, Fredolin. (2023). Assessing the impacts of climate variables on long-term air quality trends in Peninsular Malaysia. The Science of the total environment. (901. 166430. 10.1016/j.scitotenv.2023.166430).

[6] Tian Y, Liu H, Zhao Z, Xiang X, et al. (2018). Association between ambient air pollution and daily hospital admissions for ischemic stroke: a nationwide time-series analysis. PLoS Med. 2018;15(10):e1002668.

[7] K. K. Johnson, M. H. Bergin, A. G. Russell, and G. S. W. Hagler (2018). Field test of several low-cost particulate matter sensors in high and low concentration urban environments. Aerosol and Air Quality Research.

[8] Mladen K., Biljana R. S., Kire T. (2019). Internet of Things Solution for Intelligent Air Pollution Prediction and Visualization.IEEE EUROCON 2019 -18th International Conference on Smart Technologies.

[9] Tim K., Rea D., Samantha D., Royal G., Martha K., Melissa L., John P., Alison S., Kate T. (2023). Low-cost PM2.5 sensors can help identify driving factors of poor air quality and benefit communities. ISSN 2405-8440 (Volume 9, Issue 9, 2023).

[10] Tammy Noergaard (2013). Embedded Systems Architecture: A Comprehensive Guide for Engineers and Programmers. ISBN-10 0123821967.

[11] Junninen, H., Niska, H., Tuppurainen, K., Ruuskanen, J. and Kolehmainen, M. (2004). Methods for imputation of missing values in air quality data sets. Atmospheric Environment 38(18), 2895-2907.

[12] Hamza A. I. and Azman A (2015). Air quality pattern assessment in Malaysia using multivariate techniques (Malaysian Journal of Analytical Sciences ISSN 1394 – 2506).

[13] M. Budde, M. Köpke, and M. Beigl, (2016). Design of a light-scattering particle sensor for citizen science air quality monitoring with smartphones: tradeoffs and experiences. Pro Science 3: Conference Proceedings: 2nd International Conference on Atmospheric Dust - DUST 2016.Castellaneta Marina, Italy.

[14] Marek B., Piotr B., Anetta D, and Piotr M (2018). Evaluation of Low-Cost Sensors for Ambient PM2.5 Monitoring (Journal of Sensors, Volume 2018, Article ID 5096540).

[15] Ai S, Wang C, Qian ZM, Cui Y, Liu Y, Acharya BK, Sun X, Hinyard L, Jansson DR, Qin L, Lin H (2019). Hourly associations between ambient air pollution and emergency ambulance calls in one central Chinese city: Implications for hourly air quality standards (Journal Science of The Total Environment, Volume 696, 15 December 2019).

[16] Lai, Xiaozheng & Yang, Ting & Wang, Zetao & Chen, Peng. (2019). IoT Implementation of Kalman Filter to Improve Accuracy of Air Quality Monitoring and Prediction. Applied Sciences. 9. 1831. 10.3390/app9091831.

[17] Hermann Kopetz (2011). Real-Time Systems: Design Principles for Distributed Embedded Applications ISBN 9781441982377.

[18] Bilal, K.; Khalid, O.; Erbad, A.; Khan, S.U.(2018). Potentials, trends, and prospects in edge technologies: Fog, cloudlet, mobile edge, and micro data centers. Comput. Net.

[19] Sari, R.F., Rosyidi, L., Susilo, B., Asvial, M. (2021). A Comprehensive Review on Network Protocol Design for Autonomic Internet of Things. Information 2021, 12, 292. https://doi.org/10.3390/info12080292.

[20] Cuno Pfister (2011). Getting Started with the Internet of Things: Connecting Sensors and Microcontrollers to the Cloud (Make: Projects) 1st Edition. ISBN 978-1449393571.

[21] Pallavi S. and Smruti R. S. (2017). Internet of Things: Architectures, Protocols, and Applications (Journal of Electrical and Computer Engineering, Volume 2017 Article ID 9324035).

[22] Simwanda, Matamyo. (2019). Air Quality Monitoring Using Remote Sensing and GIS Applications: Exploring the Potential for Developing African Countries. Conference: WORLD ENVIRONMENT DAY COMMEMORATION 2019.

[23] Kevin Dooley (2015). The No-Sweat Guide to Network Topology.Auvik (www.auvik.com).

[24] Stawowy, M., Olchowik, W., Rosiński, A., Dąbrowski, T. (2021). The Analysis and Modelling of the Quality of Information Acquired from Weather Station Sensors. Remote Sens. 2021, 13, 693. https://doi.org/10.3390/rs13040693.

[25] J. K. Sethi and M. Mittal (2020). Analysis of Air Quality using Univariate and Multivariate Time Series Models. 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2020, pp. 823-827, doi: 10.1109/Confluence47617.2020.9058303.

[26] Joseph M. Hilbe (2015). Practical Guide to Logistic Regression. ISBN 978-1-4987-0958-3.

[27] Zhao, Z., Wu, J., Cai, F. et al.(2023). A hybrid deep learning framework for air quality prediction with spatial autocorrelation during the COVID-19 pandemic. Sci Rep 13, 1015 (2023). https://doi.org/10.1038/s41598-023-28287-8.

[28] Azid, A., Juahir, H., Toriman, M.E. (2014). Prediction of the Level of Air Pollution Using Principal Component Analysis and Artificial Neural Network Techniques: a Case Study in Malaysia (Water Air and Soil Pollution · July 2014).

[29] Prachi, Kumar N.and Matta, Gagan (2011) Artificial neural network applications in air quality monitoring and Management. International Journal for Environmental Rehabilitation and Conservation Volume II No. 1 2011 [30 – 64].

[30] Doreena D., Hafizan J., Mohd T. L., Sharifuddin M. Z., and Ahmad Z. A. (2012). Spatial assessment of air quality patterns in Malaysia using multivariate analysis (Atmospheric Environment 60 2012 172e181).

[31] Hamza A. I. and Azman A (2015). Air quality pattern assessment in Malaysia using multivariate techniques (Malaysian Journal of Analytical Sciences ISSN 1394 – 2506).

[32] K. Hundman, V. Constantinou, C. Laporte, I. Colwell, and T. Soderstorm (2018). Detecting spacecraft anomalies using LSTMs and nonparametric dynamic thresholding," in Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. London, UK.

[33] P. Malhotra, L. Vig, G. Shroff, and P. Agarwal (2015). Long short-term memory networks for anomaly detection in time series, European Symposium on Artificial Neural Networks, vol. 89.

[34] Abdullah, A. M., Abu Samah, M. A., and Jun, T. Y. (2012). An overview of the air pollution trend in Klang Valley, Malaysia. Open Environ Science 6:13-19.

[35] Department of Environment Malaysia (DOE) (2021). Malaysia Environmental Quality Report, Ministry of Science, Technology and Environment, Kuala Lumpur.

[36] Voukantsis, Dimitrios & Karatzas, Kostas & Kukkonen, Jaakko & Räsänen, Teemu & Karppinen, Ari & Kolehmainen, Mikko. (2011). Intercomparison of air quality data using principal component analysis, and forecasting of PM10 and PM2.5 concentrations using artificial neural networks, in Thessaloniki and Helsinkiinterface,".

[37] H. W. Xu, W. X. Chen, N. W. Zhao et al. (2018). Unsupervised anomaly detection via variational auto-encoder for seasonal kpis in web applications, in Proceedings of the World Wide Web Conference. Lyon, FranceA. Ito, S. Wakamatsu, T. Morikawa, S. Kobayashi (2021). 30 Years of Air Quality Trends in Japan. Atmosphere 2021. MDPI.

[38] Shaddick G, Thomas ML, Amini H, Broday D, Cohen A, Frostad J, Green A, Gumy S, Liu Y, Martin RV, et al. (2018). Data integration for the assessment of population exposure to ambient air pollution for global burden of disease assessment. Environ Sci Technol. 2018;52(16):9069–78.

[39] Y. J. Zheng, C.L. Zhang, and H. Y. Wang (2020). MTAD-TF: Multivariate Time Series Anomaly Detection Using the Combination of Temporal Pattern and Feature Pattern. Hindawi. Volume 2020 | Article ID 8846608.

[40] Mutalib, S. N. S. A., Juahir, H., Azid, A., Sharif, S. M., Latif, M. T., Aris, A. Z., Zain, S. M. and Dominick,D., (2013). Spatial and temporal air quality pattern recognition using environmetric techniques: a case study in Malaysia. Environmental Science, Processes & Impacts 15(9): 1717-1728.

[41] Shang, L., Huang, L., Yang, W. et al.(2019). Maternal exposure to PM2.5 may increase the risk of congenital hypothyroidism in the offspring: a national database-based study in China. BMC Public Health 19, 1412.

[42] Dauchet L, Hulo S, Cherot-Kornobis N, Matran R, Amouyel P, Edme JL, Giovannelli J.(2018). Short-term exposure to air pollution: associations with lung function and inflammatory markers in non-smoking, healthy adults. Environ Int. 2018;121(Pt 1):610–9.