



The Development of an Intelligent Real-time In-vehicle Air Quality Monitoring System

by

**Goh Chew Cheik
(1540211856)**

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LIST OF ABBREVIATIONS

A/C	Air Conditioner
AAA	American Automobile Association
AI	Artificial Intelligence
ANNs	Artificial Neural Networks
API	Air Pollution Index
AQHI	Air Quality Health Index
AQI	Air Quality Index
ASEAN	Association of the South East Asian Nations
AWS	Amazon Web-Service
BER	Bit Error Rate
BLE	Bluetooth Low Energy
CE	Counter Electrode
CO	Carbon Monoxide
CO ₂	Carbon Dioxide
DOE	Department of Environment
DOSH	Department of Occupational Safety and Health Malaysia
EPA	Environmental Protection Agency
FA	Fresh Air
FNNs	Feedforward Neural Networks
GPS	Global Positioning System
GRU	Gated Recurrent Unit
GSE	Gas Sensitive Electrochemical
GSS	Gas Sensitive Semiconductor
HKEPD	Environmental Protecting Department of Hong Kong
HTTP	Hyper Text Transfer Protocol
HVAC	Heating, Ventilation And Air Conditioning
I2C	Inter-Integrated Circuit
IAQ	Indoor Air Quality
IoT	Internet of Things
IV-AQMS	In-Vehicle Air Quality Monitoring System
IVMS	In-Vehicle Monitoring System

LoRa	Short For Long-Range
LR	Linear Regression
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MQTT	Message Queuing Telemetry Transport
MSE	Mean Squared Error
NaN	Not a Number
NDIR	Non-Dispersive Infra-Red
NO ₂	Nitrogen Dioxide
NO _x	Nitrogen Oxides
O ₂	Oxygen
O ₃	Ozone
PANs	Personal Area Networks
PCA	Principal Component Analysis
PIC	Programmable Interface Controller
PID	Photoionization Detector
PM	Particulate Matter
PSI	Pollutant Standards Index
UART	Universal Asynchronous Receiver/Transmitter
USB	Universal Serial Bus
R ²	Coefficient of Determination
RC	Recirculation
RE	Reference Electrode
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SO ₂	Sulfur Dioxide
SO ₃	Sulfur Trioxide Gas
SPI	Serial Peripheral Interface
SVM	Support Vector Machines
SVR	Support Vector Regression
VOC	Volatile Organic Compounds

WE	Working Electrode
WHO	World Health Organization
Wi-Fi	Wireless Fidelity

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LIST OF SYMBOLS

β	Matrix weight
ε	Bias
\hat{y}	The predicted value
x_n	The nth feature value
θ_j	The jth model parameter
x_i	i-th training instance
y_i	Training label
ξ_i	Distance between the bounds and predicted values outside the bounds
\bar{y}_i	Mean value of y
Z_i	Rescaled value in i th position
\bar{x}	Mean of the feature vector
σ	Stand deviation of the feature vector

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Pembangunan Sistem Pemantauan Pintar Kualiti Udara Dalam Kenderaan Pada Keadaan Sebenar

ABSTRAK

Kesedaran masyarakat mengenai tahap kualiti udara semakin meningkat terutama dari segi kualiti udara di dalam kabin kenderaan. Kualiti udara di dalam kabin kenderaan dipengaruhi oleh beberapa gas, seperti karbon dioksida (CO₂), zarah-zarah habuk (PM), nitrogen dioksida (NO₂), sulfur dioksida (SO₂), ozon (O₃) dan karbon monoksida (CO). Sebahagian gas tersebut dihasilkan oleh ekzos kenderaan dan berbahaya kepada kesihatan. Kebanyakan pemandu dan penumpang biasanya menutup tingkap dan menggunakan mod peredaran semula bagi sistem pengudaraan kenderaan tersebut. Dalam keadaan yang tertutup itu, sumber utama pencemaran udara adalah penghuni kenderaan sendiri yang menghasilkan karbon dioksida sebagai bahan pencemar yang dikenali sebagai biofluen manusia. Kepekatan karbon dioksida yang tinggi mengurangkan kemampuan kognitif manusia, menyebabkan pening dan keletihan. Pening dan keletihan boleh meningkatkan risiko pemandu mengalami kemalangan. Akibatnya, keadaan ini mendatangkan bahaya kepada penghuni kereta, dan juga pengguna jalan raya yang lain. Sistem pemantauan kualiti udara yang sedia ada tidak menyediakan indeks kualiti udara di dalam kenderaan dan tiada pemantauan dan ramalan kualiti udara semasa di dalam kabin kenderaan. Oleh itu, kajian ini telah membangunkan sebuah sistem pemantauan yang dikenali sebagai sistem pemantauan kualiti udara di dalam kenderaan (IV-AQMS) yang telah digunakan untuk mengumpulkan data kualiti udara di dalam kenderaan. Sistem tersebut mempunyai pangkalan data berasaskan awan yang dibangunkan bagi menyimpan data kualiti udara masa nyata dari kenderaan yang dipilih. Data yang diperolehi dari sistem ini kemudiannya digunakan untuk meramal kualiti udara di dalam kabin kenderaan dengan mod pengudaraan peredaran ulang dengan tujuan untuk mengelakkan penghuni kenderaan berada dalam kondisi kualiti udara yang tidak baik. Dengan menggunakan model pembelajaran mesin yang berbeza dan pembelajaran mendalam, tahap kualiti udara dalam kenderaan selama lima minit, sepuluh minit dan dua puluh minit masa hadapan dapat diramalkan. Model ramalan Gated Recurrent Unit (GRU) yang dicadangkan didapati sebagai model ramalan yang paling sesuai bagi aplikasi ini kerana ia mempunyai nilai pekali penentuan (R^2) tertinggi sebanyak 0.97 dan nilai ralat kuasa dua punca (RMSE) terendah sebanyak 2.54 berbanding dengan model kecerdikan buatan yang lain.

The Development of an Intelligent Real-time In-vehicle Air Quality Monitoring System

ABSTRACT

Public awareness about the level of air quality has gradually increased especially the air quality inside a vehicle cabin. Air quality inside a vehicle cabin is affected by several gases, namely, carbon dioxide (CO₂), particulate matter (PM), nitrogen dioxide (NO₂), sulphur dioxide (SO₂), ozone (O₃) and carbon monoxide (CO). Majority named gases are contributed by exhaust gas and those gases are harmful to health. Most of the drivers and passengers usually shut the windows and switch the vehicle's ventilation system into recirculation mode. In such confined space, pollution source mainly comes from occupants, whom produce carbon dioxide as contaminant known as human bioeffluent. The high concentration of carbon dioxide reduces human cognitive ability, causing dizziness and fatigue. Dizziness and fatigue can increase the driver's risk of getting into car accident. Consequently, this situation bring danger to the occupants, and to other potential road users as well. Existing air quality monitoring system does not provide in-vehicle air quality index and real-time monitoring and prediction of in-vehicle air quality. Therefore, this study developed a system named in-vehicle air quality monitoring system (IV-AQMS) that has been used to collect the air quality level inside the vehicle cabin. The system also includes a cloud-based database that stores the real-time air quality data from the targeted vehicles. The data obtained from the system was then used to predict future air quality inside a vehicle cabin with the recirculation ventilation mode with the purpose of avoiding vehicle occupants to stay in poor air quality environment. A dedicated in-vehicle air quality monitoring system has been developed. By using different models of machine learning as well as deep learning, the future air quality level in the vehicle for five minutes, ten minutes and twenty minutes time slot have been predicted. The proposed Gated Recurrent Unit prediction model is found as the most suitable prediction model for this application because it has the highest coefficient of determination value (R^2) of 0.97 of and low root mean squared error (RMSE) value of 2.54 compared with other artificial intelligence models.

CHAPTER 1 : INTRODUCTION

1.1 Research Background

Air quality can be described as the condition of the air within our surrounding. Good air quality might protect human's lung free from contaminated air while poor air quality can affect or harm human health and the environment. World Health Organization (WHO) stated that an estimated seven million premature deaths yearly in the world due to poor air quality caused by air pollution (World Health Organization, 2016). Generally, air quality is the different composition of gases exist around the targeted environment which can be classified as indoor and outdoor environments.

The indoor environment could be further classified into static space, such as inside of a building, or a moving space, such as vehicle's cabin. During the past decades, most research has focused on the air quality outside of the vehicles. Researchers are coming to the realization that the air inside the vehicle could be worse. Poor air quality within the vehicle cabin not only can influence the occupants' comfort level and cognitive level, but beyond this, it can also cause immediate health issues and serious illnesses (Requia et al., 2018; Schnell et al., 2019).

The American Automobile Association (AAA) Foundation for Traffic Safety found that time spent, and the distance travelled by human inside a vehicle increases by the education levels. A grade school person spends their time inside vehicle an average of 32 minutes while a college graduated person spends an average of 58 minutes daily (Johnson, 2015). Association of the South East Asian Nations (ASEAN) has summarized the statistics of road traffic crash and death rate in Malaysia that shows 489,606 road

crashes and 6706 fatalities in 2015 (Kamaluddin et al., 2019). The Royal Malaysia Police has stated that the leading causes of a road crash are drivers in fatigue condition and distracted driving (Kumar, 2018). The AAA estimates that one out of every six deadly traffic accidents, and one out of eight crashes requiring hospitalization of car drivers or passengers due to drowsy drivers (Colic et al., 2014). Several studies show that the air quality inside a vehicle cabin possibly contains pollutants such as particulate matter (PM) and hazardous gases such as volatile organic compounds (VOC), carbon monoxide (CO), nitrogen dioxide (NO₂), sulphur dioxide (SO₂), carbon dioxide (CO₂) and other pollutants (Chang et al., 2018; Harik et al., 2017; Xu et al., 2018). That are sometimes higher than the limits set by the World Health Organization (WHO) and the US Occupational Safety and Health Administration (US OSHA) that causes immediate health issues, including impaired vision and coordination, nose and throat irritations, headaches, dizziness, drowsiness and fatigue to the occupants. The combinations of these effects to the human health are not ideal for operating a vehicle.

The newer generation of vehicles has put much effort into the Heating, Ventilation and Air Conditioning (HVAC) system by providing fresh air mode or recirculation (RC) mode option to the occupants (Ramesh, 2013). The fresh air mode introduces outside air into the car by opening air duct. In the recirculation mode, air in the vehicle cabin can be recirculated to maintain comfortable ventilation rates and to help maintain good indoor air quality by isolating outside air pollutants from streaming into the vehicle cabin.

In the early 2000s, a technology called in-vehicle monitoring system (IVMS) (Pooja, 2013; Vineth et al., 2019) was introduced as a way to reduce road accidents (Sampoornam et al., 2021), road fatalities (Battiato et al., 2018), and encourage safe

driving behaviour (Guo et al., 2018; X. Wang & Kostyniuk, 2018) by installing an electronic device with built in software in the vehicle to enable location tracking, vehicle metrics and monitoring driver activities and behaviours. The focus of this research is to develop a monitoring system that not limited to real-time vehicle tracking, but also with the ability to monitor in-vehicle air quality with predictive analytics. The aims are to receive updated air quality information inside a vehicle cabin in real-time and to predict the future concentration of the indoor air pollutants. By introducing artificial intelligent prediction algorithms, data collected from the real-time cloud-based in-vehicle air quality monitoring system (IV-AQMS) system is used to predict future in-vehicle air quality. Following section further elaborates on the problem that wants will be solved by this research.

1.2 Problem Statements

In recent years, there are increasing number of vehicle crashes occurred due to drowsy drivers, fatigue, and behavioural mistakes. There is much concern that poor air quality within the vehicle cabin is the main cause of this issue (Chen et al., 2020; Hudda & Fruin, 2018; Magaña et al., 2020). While using the fresh air mode of HVAC system introduce air pollution from the outside such as PM, NO₂, SO₂ and CO into the vehicle cabin, the RC mode reduce the air pollution by circulating the air inside the vehicle cabin. However, RC mode will cause passenger-exhaled CO₂ to accumulate rapidly which can significantly reduce decision-making performance, and may cause drowsiness (Jacobson et al., 2019). Since most of the major air pollutants are invisible, people are not aware of the air quality inside the vehicle cabin. There is a limited study done to study the types of pollutants exist in the vehicle cabin in RC and fresh air mode, at different speed and different number of occupants in the vehicle. Fleet management system utilizing IVMS

system is gaining popularity for location tracking and driver activity monitoring to ensure safety and increase productivity. Although these approaches have made significant contributions to the safety and quality of life of the vehicle occupants, the real-time monitoring, prediction, and interactive visualizations of in-vehicle air quality are still immature and remain challenging. This is because there is no established in-vehicle air quality index and the real-time monitoring, prediction, and interactive visualization of the air quality inside vehicle cabin is still immature. Accurate prediction of the future in-vehicle air quality and the air quality index requires real-time information about the concentrations of pollutants exist in the vehicle with other parameters, and this kind of data is not necessarily available in an online, constantly updated database. This project proposes to design and develop a cloud-based real-time air-quality measurement and analysis that provides a prediction of future air quality and an air quality index that is easy to visualize and understand by the occupants inside the vehicle. The gap identified are as follow:

- a) There is no system proposed to collect and store the real-time value of gas concentration inside the car with temperature, humidity, location, and speed with interactive visualizations.
- b) There is no air quality standard for the in-vehicle air quality index.
- c) Limited amount of research done to predict the future in-vehicle air quality using machine learning or deep learning methods.