Real-time Route Planning using Mobile Air Pollution Detectors and Citizen Scientists

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***Abstract*—The increasing urbanization of society is resulting in numerous challenges. One of these challenges is transport congestion and the associated increase in pollution that is widely accepted as driving global warming. For many individuals and especially those with respiratory issues, e.g., those with asthma or chronic obstructive pulmonary disease, high levels of pollution can cause direct health events. The ability to measure pollution accurately in real time at disaggregated levels and subsequently avoid pollution hotspots is thus highly desirable. This paper describes a Cloud-based infrastructure and associated mobile application that utilizes real time, mobile pollution measurement technology to help individuals avoid pollution hotspots through real-time pollution-aware routing algorithms. (*Abstract*)**

Keywords—Air pollution, Route planning, Airbeam technology, Particulate Matter.

I. INTRODUCTION (*HEADING 1*)

In recent years, air pollution has become an increasing problem as more and more people live in cities that are continually increasing in size. There are many challenges in such urbanisation with one major issue being traffic. Traffic congestion is an all too familiar problem facing major cities, especially given the continual dependence on fossil fuel-based cars. Such concentration of vehicles gives rise to pollution from exhausts that can have direct health impacts. Kim et al [1] found that major pollutants in air, such as volatile organic compounds, particulate matter and even biological matter such as dust mites directly contribute to and indeed often exacerbate diseases like asthma and allergies. Similarly, Ebba et al [2] found that air pollution is directly associated with increasing likelihood of premature babies and poor fetal growth.

One of the major air pollutants from vehicles and indeed industry, is small particulate matter (PM). Small particles emitted from car exhausts and burning of fossil fuels within coal fire-based power stations are a major source of pollution. Such particles can be measured at different sizes including PM1.0 (particles of 1 micron diameter), PM2.5 (particles up to 2.5 microns in diameter) and PM10 (particles up to 10 microns in diameter). The number of particles is typically measured in given concentrations (micrograms of given particle type per cubic metre).

At present such air quality pollution information is captured by government organisations such as the Environmental Protection Authority (EPA - www.epa.vic.gov.au). However, the data they collect is based on fixed locations. The distribution of these air quality data collection for sites around Melbourne is shown in Fig. 1. This data is subsequently used to provide a spread of information regarding pollution using approaches such as Kriging and interpolation [3]. However, such an approach ignores the real-world challenges of dispersal of air pollution. For example, one street can be highly polluted whilst a parallel street that is metres away can have minimal pollution based on the traffic patterns, the building facades and wind direction. The ability to capture such disaggregated air pollution data anywhere and in real time is thus highly desirable.

Fig. 1: Location of Air Quality Stations Around Melbourne (EPA 2021)

Many portable air pollution sensors have been developed to help people capture and understand localised air pollution. Aircasting (https://www.habitatmap.org/aircasting) is an end-to-end, open-source platform that uses Airbeam technology to record, share and display such environmental data. The devices capture a range of data including PM10, PM2.5, PM1.0, temperature, humidity and sound information. The devices are connected (via Bluetooth) with an Android app and capture second by second data. The apps use the location service in the phone for associated geolocation information. Such data can then be pooled together to provide aggregated data across given regions at a much higher spatial accuracy than would ever be possible using the data collection sites in Fig. 1.

Fig. 2 shows an example of individual Airbeam data collected by the author as part of their daily commute (on a scooter) from the suburbs to the city centre Central Business District (CBD). As seen, the level of pollution increases (red line) towards the Melbourne CBD where there are many more people, cars and skyscrapers that lock in air pollution and hence concentrate the pollution levels. It should also be noted that by and large Melbourne has extremely good air quality, but this is not always the case in the city centre and especially when external events take place such as thunderstorm asthma and bushfires – an increasingly common phenomenon in Australia.

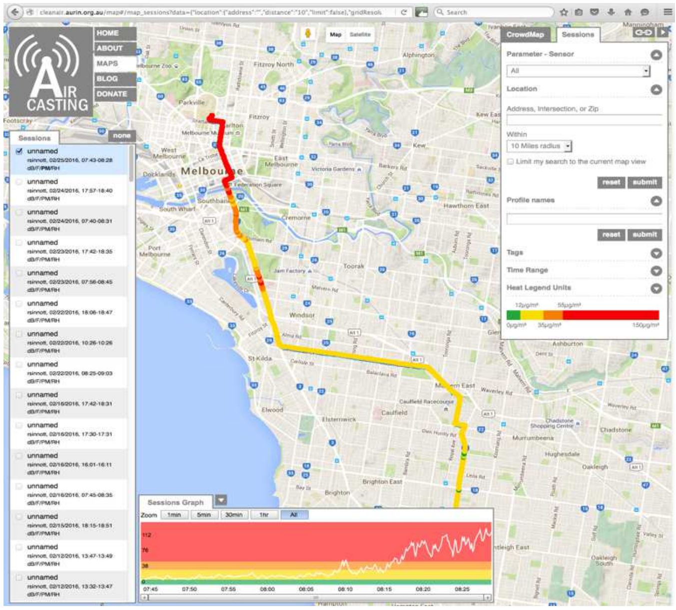

Fig 2: Airbeam data collection for individual commute of citizen scientist

The real time aggregation of such data can be used to provide much more accurate air pollution data. This can be used for many things, e.g., warning people about excessive air pollution in specific streets and avoiding routes that are highly polluted would be advantageous.

In this paper we described the realisation of a real time pedestrian routing algorithm that factors in pollution levels both at the start of a journey and as the pollution evolves throughout the journey. To ensure sufficient real time data was available, we focus specifically on the Melbourne CBD. This is the area that has the highest levels of pollution and also the most data collected using the Airbeam technology by Melbourne-based citizen scientists.

The rest of the paper is structured as follows. Section II considers related work. Section III considers the pollution data collection process. Section IV presents the realisation of the mobile app that supports real-time pollution aware routing, and finally section V concludes the work and identifies potential areas of future work.

II. Related Work

Air pollution has been a topic of major concern in recent years and a source of big data research challenges due to the size, volume and velocity of production/consumption. It is now widely recognised that the main sources of air pollution in cities stem from cars and burning of fossil fuels amongst other environmental factors, e.g., bushfires [4].

Huang et al [5] explored pollution prediction based on Long Short Term Memory (LSTM) using a range of features in the data. Guan [6] explored big data analytics of a range of air pollution data sets including use of different models including linear regression, Artificial Neural Networks (ANN) and LSTM recurrent neural networks. They found that LSTM performed best and was able to predict high PM2.5 values with reasonable accuracy, whilst ANN and linear models have drawbacks in prediction of high PM2.5 values however they offered reasonable overall performance.

Zhang et al [7] found that the accumulative effect of both medium-term-low-intensity over-exposure and shorter term, high-intensity exposure to PM pollutants posed serious threats to individuals. Lina et al [8] identified that PM 2.5 specifically often contained several kinds of heavy metals and the long-term accumulation of such heavy metals pose a great threat to people.

In terms of routing and route planning, an A-star based mobile dynamic vehicle navigation system was developed by Shahzada and Askar [9]. This application considered dynamic and changing road conditions. The system had a range of functionalities including panning and zooming, geocoding, reverse geo-coding and routing. Nana et al [10] put forward a mobile phone application based on the ZigBee technology, which was able to monitor and control real-time intelligent systems remotely with specific focus on measurement of the concentration of PM2.5. However, such apps simply recorded levels of PM2.5 and not how to avoid hotspots nor how such real time changes to the routes using evolving data could be supported.

Bell [11] proposed a multi-path A-star algorithm called Hyperstar for risk averse vehicle navigation. Wang and Xiang (2018) improved the A-star algorithm through incorporation of a range of orientation constraints. Ghose et al. [12] proposed a thin-client approach and associated set of metrics suitable for navigation using mobile devices. Sharma and Gandole [13] improved the thin client performance by reducing network latency and hence improved the speed of access to real time data. Neither of these works focused on pollution avoidance, however.

Alam et al [14] showed that air pollution exposure data could be used as a targeted travel cost in route selection. They found that routing results based on travel time, distance and carbon dioxide levels were similar, but PM10 could cause a small increase in these values. They did not attempt to quantify the total amount of exposure to air pollution nor show how evolving data would impact the routes that were proposed.

Vamshi and Prasad [15] demonstrated that routing only based on shortest distances causes traffic congestion in urban areas, and traffic junctions especially, i.e., where vehicles are more likely to be stationary, which subsequently lead to higher levels of air pollution. They proposed a dynamic route planning algorithm to balance the traffic flow to reduce the air pollution exposure based on minimising the number of junctions traversed and hence minimising locations with higher pollution.

The algorithms above are mostly based on indirect air pollution data and use of non-real-time data. Air pollution mobile apps only provide feedback of monitored air pollution data to users at an aggregated level at best and they do not make use of real-time disaggregated data that can be used for decision making and avoidance of air pollution hot spots that evolve in real time at the street level. In this paper, we present a mobile application and routing system that use real-time air pollution data collected by portable air pollution sensors to calculate the least polluted exposure routes between two given locations. We focus here on the Melbourne CBD however the app can in principle be used wherever real time pollution data is being captured.

III. Data Collection

The air pollution data used in this paper was sourced from a targeted version of the Aircasting platform hosted at the University of Melbourne and involving citizen scientist (users_ of the Airbeam technology. As mentioned, to ensure that sufficient data was available we focused on the Melbourne CBD. The main reason for this is the adoption of the Airbeam solutions for real time air quality data capture is not widespread across the population. It is also the case that far more people live in the CBD and the traffic is far denser and more congested compared to the suburbs. There are also many more pavements and shops in the CBD where people will walk and thus able to benefit from real-time route planning and avoiding higher levels of pollution where possible. The Melbourne CBD itself is a moderately sized area of approximately 1km*1.8km (see Fig. 4) and hence this can be walked from corner-corner in a relatively short time-period (approx. 30mins).

We selected PM2.5 as the indicator to reflect the concentration of air pollution and not all PM that can be collected by the Airbeam technology. This choice was made in part by the previous versions of the Airbeam technology only supporting PM2.5. More recent versions of the devices support PM1.0 and PM10. The raw data pollution data is stored in a mySQL database and call be pulled in real time to the mobile application through a targeted API. An example of the data in CSV format is shown in Fig. 3. This includes a timestamp, the latitude/longitude and the actual value of the PM2.5 recording.

	A	B	C	D	E	F
1	AirBeam2-PM2.5	AirBeam2:001896108040	Particulate Matter	micrograms per cubic meter	**Flinders St**	
2	Timestamp	geo:lat	geo:long	Value		
3	2019-01-20T16:49:21.217+1100	-37.81521493	144.9746181	2		-37.8152149321537,144.974618066912
4	2019-01-20T16:49:21.714+1100	-37.81521493	144.9746181	2		-37.8152149321537,144.974618066912
5	2019-01-20T16:49:22.712+1100	-37.81521457	144.9746185	2		-37.815214567,144.974618457
6	2019-01-20T16:49:23.709+1100	-37.81521593	144.9746188	2		-37.815215934,144.974618753
7	2019-01-20T16:49:24.707+1100	-37.81521713	144.9746168	2		-37.815217127,144.974616792
8	2019-01-20T16:49:25.704+1100	-37.81521974	144.9746169	2		-37.815219735,144.974616882
9	2019-01-20T16:49:26.702+1100	-37.81521974	144.9746169	2		-37.815219735,144.974616882
10	2019-01-20T16:49:27.699+1100	-37.81521974	144.9746169	1		-37.815219735,144.974616882
11	2019-01-20T16:49:28.697+1100	-37.81521974	144.9746169	1		-37.815219735,144.974616882
12	2019-01-20T16:49:29.694+1100	-37.81521974	144.9746169	1		-37.815219735,144.974616882
13	2019-01-20T16:49:30.692+1100	-37.81522603	144.9745866	1		-37.815226027,144.974586563
14	2019-01-20T16:49:31.690+1100	-37.81522791	144.9745764	1		-37.815227909,144.974576439
15	2019-01-20T16:49:32.687+1100	-37.81523108	144.9745658	1		-37.815231082,144.974565765
16	2019-01-20T16:49:33.686+1100	-37.81523443	144.974554	1		-37.815234431,144.974553993
17	2019-01-20T16:49:34.683+1100	-37.81523832	144.9745411	1		-37.815238323,144.974541087
18	2019-01-20T16:49:35.681+1100	-37.81524198	144.974527	2		-37.81524198,144.974526983
19	2019-01-20T16:49:36.678+1100	-37.81524587	144.9745111	2		-37.815245872,144.974511128
20	2019-01-20T16:49:37.675+1100	-37.81524985	144.9744963	2		-37.815249848,144.974496301
21	2019-01-20T16:49:38.673+1100	-37.81525322	144.9744819	2		-37.815253224,144.974481893
22	2019-01-20T16:49:39.671+1100	-37.8152559	144.9744661	2		-37.815255901,144.974466111
23	2019-01-20T16:49:40.670+1100	-37.81525849	144.9744495	2		-37.815258494,144.974449521
24	2019-01-20T16:49:41.667+1100	-37.81526071	144.9744329	2		-37.815260706,144.974432933
25	2019-01-20T16:49:42.666+1100	-37.81526222	144.9744178	2		-37.815262219,144.974417788
26	2019-01-20T16:49:43.661+1100	-37.8152636	144.9744028	2		-37.815263602,144.974402765
27	2019-01-20T16:49:44.659+1100	-37.81526613	144.9743869	2		-37.815266134,144.974386919
28	2019-01-20T16:49:45.657+1100	-37.81527009	144.97437	2		-37.815270092,144.974370025
29	2019-01-20T16:49:46.654+1100	-37.81527415	144.9743531	2		-37.81527415,144.974353098
30	2019-01-20T16:49:47.651+1100	-37.81527693	144.9743353	2		-37.815276933,144.974335332

Fig. 3. Sample of the raw air pollution data

The streets in the Melbourne CBD are naturally intertwined and cut into small blocks. Each crossing and street segment was mapped into a Java object to implement the route planning algorithm. The mean value of PM2.5 of each street segment is continuously calculated based on the data captured by citizen scientists. Where no new data was available, historical average data was used for the algorithm. Based on these mean values, we defined and colour coded three ranges of pollution exposure levels based on historical averages specific to the Melbourne CBD:

- green (good) - PM2.5 lower than 2 $\mu g/m^3$
- yellow (medium) - PM 2.5 between 2-5 $\mu g/m^3$
- red (poor) - PM 2.5 higher than 5 $\mu g/m^3$

It is noted that the CBD has historically seen PM2.5 pollution levels over 300 PM $\mu g/m^3$, however such events are rare, e.g., during bushfires. The colour coded pollution levels for a typical mid-day during the working week for the CBD are shown in Fig 4.

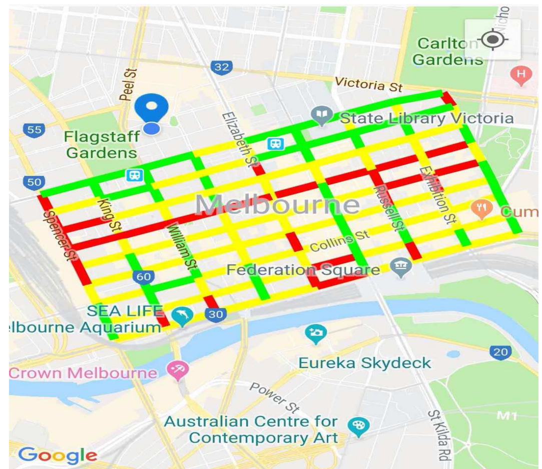

Fig 4. Pollution levels across the CBD

IV. Implementation of the Routing Algorithm

The solution for pollution-avoiding route planning is realized through an Android mobile application. The app was required to support several core scenarios:

1. A user uses the app to find their current location.
2. The user sets their current location as a starting point and types (or selects on the map) another location as their intended destination.
3. The least polluted route is calculated and shown.
4. The user walks along the calculated path to reach their intended destination.
5. As the user walks along the selected path, the route is continuously assessed and updated based on the real time updates to the pollution data from citizen scientists, and if needs be alternative (better) routes are calculated.
6. The distance and pollution exposure of the routes are shown to the user for them to make decisions on the specific route to take.

After choosing a starting point and intended destination, the user has the choice of either minimizing pollution exposure or minimizing the distance by clicking two buttons on the top of the map. Fig. 5 shows the difference between air pollution routing and normal routing.

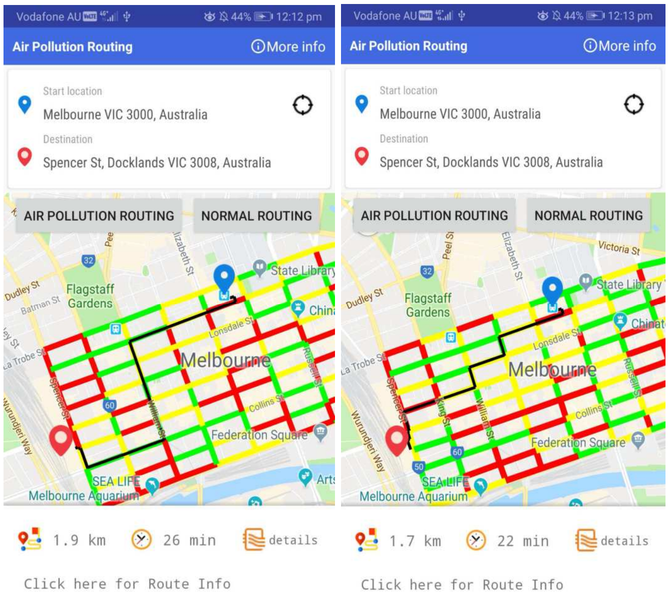

Fig. 5. Difference between air pollution routing (left) and normal routing (right)

To support this real time route planning, the algorithm realises the A-Star algorithm as the basis for the path finding method. The A-Star algorithm is one of the most popular heuristic search algorithms. It aims to find the path with the least cost from a given starting point to a given end point. In this work, the cost is based on the air pollution exposure and walking distance based on normal routing - typically the shortest distance. To support this, we use information on the roads and intersections of Melbourne CBD. Fig. 6 shows that there are 81 intersections and 144 road sections in the Melbourne CBD. Each segment of road will have an associated pollution level that is recorded and continually updated.

Fig. 6. Intersections and road sections in the Melbourne CBD

Each intersection shown in Fig. 6 has an id and associated geographic information. Each road section includes the length of the road and the current pollution index based on the average PM 2.5 value for that stretch of road. This average can be a historic average of the average of real time updates from multiple citizen scientists. The A-star algorithm proposes routes based on the actual cost from the start and an estimated cost value to the end of the path. This cost can be based on distance or other factors (such as pollution).

The primary difference between air pollution routing and normal routing is how cost is calculated. The cost in air pollution routing is equal to the distance of the road multiplied by the average PM2.5 value for that stretch road. Thus, a long road with higher pollution value will lead to larger associated cost. The algorithm is continually updated with new data and recalculates the route with the least overall cost to the intended destination based on the length of the route and the accumulated pollution for the different paths that might be taken. The cost in normal A-star routing is based solely on the distance of the road, i.e., the shortest path is generally the preferred path.

After finding the optimal route based on the extended A-Star search algorithm, it is necessary to show the calculated route to the user and provide them with detailed information. The Google API is used to draw the calculated route on the map. A URL request is sent to the http-based Google API. The URL string includes the latitude/longitude information of the starting point and destination, together with waypoints at the relevant intersections. After fetching the response, polylines are drawn on the map that show the routing information through decoding the returned JSON object.

The app also provides detailed routing information that can be displayed to the user at the bottom of the screen. Fig. 7 (left) shows the detail routing information and Fig. 7 (right) shows the total accumulated pollution exposure based on the route taken and the remaining route at that specific time together with the time taken in walking along the calculated route up to that point.

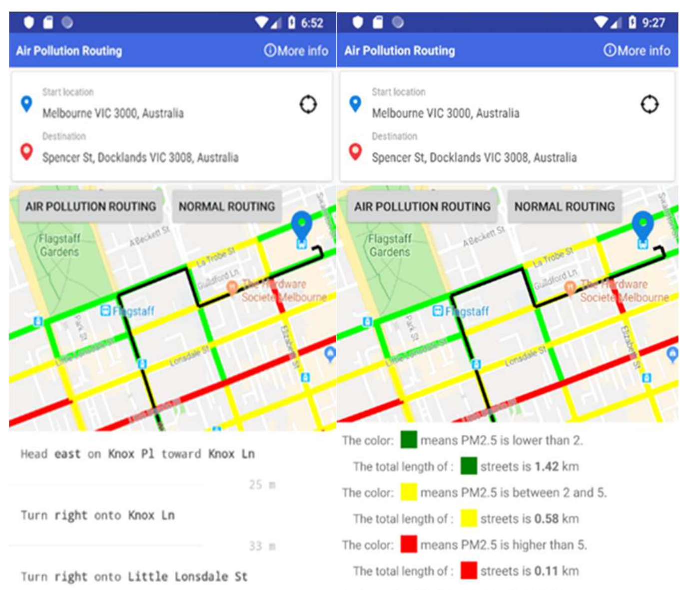

Fig. 7. Detailed routing information (left) and accumulated exposure (right)

V. DISCUSSION

The current realization of the mobile app demonstrates that the algorithm does indeed produce routes that minimize routes based on their air pollution levels. One of the challenges with this work is the amount of actual citizen scientists and hence data that is available to drive these real-world scenarios. The Airbeam technology works and accurately captures pollution information [16]. However, the devices are not cheap and unlikely to be adopted by the population at large. Organisations such as the EPA are currently exploring these devices as a mechanism to provide real time air pollution data at a disaggregated level. Such systems are not intended to replace the more accurate and more costly systems that are in place (as shown in Fig. 1) but to augment them with other sources of data. Activities are underway to use Internet of Things (IoT) devices for measuring air pollution at specific locations around Victoria – most notably on major thoroughfares where the devices are attached to overhead lighting and signage.

The work described here is based on actual data collected by Airbeam devices from citizen scientists (approx. 3Gb data) however to demonstrate the real time evolving nature of pollution and the impact on the route-finding algorithm, this data is used to generated (seed) more data for the specific locations across the CBD. Ideally this representative but simulated data would not be necessary and official sources of such data would be directly accessible from given agencies. It is noted that other Government departments are making increased amounts of data available across Australia. For example, VicRoads (Department of Transport) now provide access to daily traffic patterns based on Bluetooth-based data captured across the road network. Such data is released on a daily basis however, this is after the fact and live access to real time traffic movement data is not yet supported. Such live data would be essential for an app such as this that calculated and provides live routing information.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have realised a route planning algorithm using real time air pollution data collected by citizen scientists using Airbeam devices. This was delivered through an Android-based mobile application. Although recommended routes can sometimes be slightly longer than the shortest routes, we have shown how the algorithm can minimize people's exposure to air pollution. For many people, e.g., those with asthma, this may be a choice they are willing to make.

The current version of the mobile app uses the Melbourne CBD as the focus area. The algorithm has been designed for scalability and larger scale routes have been demonstrated, e.g., involving routes outside of the CBD, however the benefit of large-scale route needs to be considered in terms of the diffusion of air pollution. Thus, the pollution levels at the start of a 5km walk that traverses the Melbourne CBD may bear no resemblance to the pollution levels towards the end of the walk.

There are various ways that the work here can be improved. One obvious one is introducing air pollution prediction mechanisms, using real-time air pollution data and taking traffic flow information. Big data pollution platforms for real time traffic analytics using Docker/Kubernetes Cloud scaling have been explored in [17,18].

Given the real time high volume and high velocity demands arising from potentially thousands of citizen scientists, there is a need for stream-based data processing solutions that scale. Work has explored streaming technology platforms such as Kafka [19] and demonstrated how Cloud infrastructure can scale up and down as needs be, e.g., more resources are needed and used during rush hour.

Air pollution can have many health impacts. Understanding the impacts of air pollution exposure on lung cancer or other respiratory conditions would be an obvious extension to this work. Drawing on projects such as the Australian Urban Research Infrastructure Network (AURIN – www.aurin.org.au), a wide range of definitive Government data sets are now widely accessible. Fig. 8 shows the incidence of lung cancer across Victoria using data from the Victorian lung cancer registry and other resources that may in part explain this distribution.

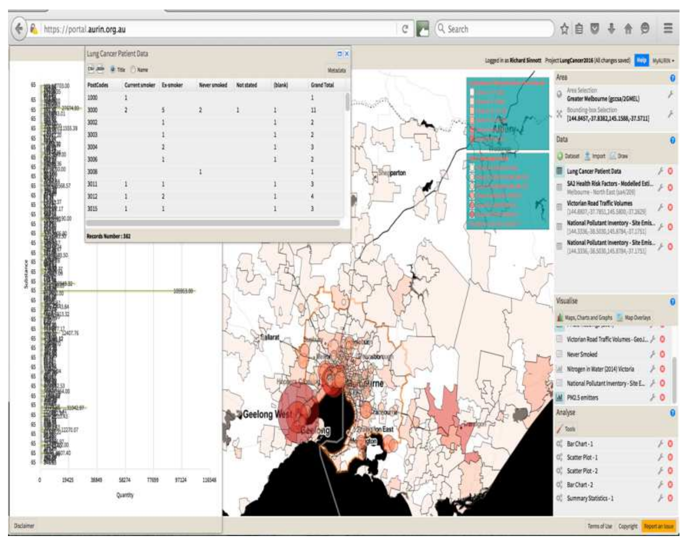

Fig. 8. Lung cancer patient distribution across Victoria

Fig 8 shows the number of patients per postcode in the choropleth map with darker reds indicating more patients; the centroids show the factories that pollute (PM2.5). Not visibly shown is the number of vehicles travelling on the road network across Victoria. In short, the potential for use of such air pollution data to be captured and used together with other data sets is directly possible.

Further extensions to the work include the use of app-based notifications related to higher levels of pollution. This could be used to tackle ad hoc major pollution events such as those caused by bushfires and or thunderstorm asthma. Numerous people died as a result of the last major incident of thunderstorm asthma in Melbourne in 2016 [20].

Acknowledgments

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The source code for this project is available at: https://github.com/flhsyuan/AirPollutionRouting.

A video demonstrating the mobile application is available at: https://www.youtube.com/watch?v=8F58lNTDHV4.

The Android APK of the mobile application is available at: https://github.com/flhsyuan/AirPollutionRouting/blob/master/app-debug.apk.

References

[1] Kim, K., Jahan, S., Kabir, E. (2013). A review on human health perspective of air pollution with respect to allergies and asthma. Environment International, Sept 2013 59:41-52

[2] Ebba, M., Anna, R., Håkan, T., Jonas, B., Emilie, S., Kristina, J., Raff, R., Lars, R. (2011). Maternal Exposure to Air Pollution and Birth Outcomes. Environmental Health Perspectives. 119(4):553-558.

[3] Van Beers, W. C., & Kleijnen, J. P. (2004, December). Kriging interpolation in simulation: a survey. In *Proceedings of the 2004 Winter Simulation Conference, 2004.* (Vol. 1). IEEE.

[4] EPA Victoria. (2017). PM2.5 particles in air, https://www.epa.vic.gov.au/your-environment/air/air-pollution/pm25-particles-in-air

[5] Huang, C. and Kuo, P. (2018). A Deep CNN-LSTM Model for Particulate Matter (PM2.5) Forecasting in Smart Cities. Sensors, 18(7), p.2220.

[6] Guan, Z., Sinnott, R.O., Prediction of Air Pollution through Machine Learning, IEEE/ACM International Conference on Big Data Computing, Applications and Technologies (BDCAT), Zurich, Switzerland, December 2018.

[7] Zhang, A., Qi, Q., Jiang, L., Zhou, F., Wang, J. (2013). Population exposure to PM2.5 in the urban area of Beijing. Plos One [PLoS One] 2013 May 02; Vol. 8 (5), pp. e63486. Date of Electronic Publication: 20130502 (Print Publication: 2013).

[8] Lina, S., Xun, X., Xiao Yang, D., Xudong, Z. (2014). The Research Progress Of Heavy Metals In PM2.5. Advanced Materials Research; 2014, Vol. 955-959, p1397-1404, 8p.

[9] Shahzada, A., & Askar, K. (2011, December). Dynamic vehicle navigation: An A* algorithm based approach using traffic and road information. In 2011 IEEE International Conference on Computer Applications and Industrial Electronics (ICCAIE) (pp. 514-518). IEEE.

[10] Nana, L., Guoliang, Z., Kuan, L., Shaolei, Z., Yubo, Y., Dongyao, Z. (2018). Mobile Phone APP Remote Real-time Monitoring and Control Intelligent Building System Based on ZigBee, Chinese Automation Congress (CAC) Automation Congress (CAC), 2018 Chinese. :2923-2927 Nov, 2018.

[11] Bell, M. G. (2009). Hyperstar: A multi-path Astar algorithm for risk averse vehicle navigation. Transportation Research Part B: Methodological, 43(1), 97-107.

[12] Ghose, T., Namboodiri, V., & Pendse, R. (2015). Thin is green: Leveraging the thin-client paradigm for sustainable mobile computing. Computers & Electrical Engineering, 45, 155-168.

[13] Sharma, S. U., & Gandole, Y. B. (2014). Virtualization approach to reduce network latency for thin client performance optimization in cloud computing environment. In International Conference on Computer Communication and Informatics (pp.1-6). IEEE.

[14] Alam, M. S., Perugu, H., & McNabola, A. (2018). A comparison of route-choice navigation across air pollution exposure, CO2 emission and traditional travel cost factors. Transportation Research Part D: Transport and Environment, 65, 82-100.

[15] Vamshi, B., & Prasad, R. V. (2018, February). Dynamic route planning framework for minimal air pollution exposure in urban road transportation systems. In 2018 IEEE 4th World Forum on Internet of Things (WF-IoT) (pp. 540-545). IEEE.

[16] Mukherjee, A., Stanton, L. G., Graham, A. R., & Roberts, P. T. (2017). Assessing the utility of low-cost particulate matter sensors over a 12-week period in the Cuyama valley of California. *Sensors*, *17*(8), 1805.

[17] Gong, Y., Morandini, L., Sinnott, R.O., The Design and Benchmarking of a Cloud-based Platform for Processing and Visualization of Traffic Data, IEEE International Conference on Big Data and Smart Computing, Jeju Island, Korea, February 2017.

[18] Gong, Y., Rimba, P., Sinnott, R.O., RT-DBSCAN: Real-time Parallel Clustering of Spatio-Temporal Data using Spark-Streaming, International Conference on Computational Science (ICCS 2018), Wuxi, China, June 2018.

[19] Truong, T., Harwood, A., Sinnott, R.O., Chen, S., Performance analysis of large-scale distributed stream processing systems on the Cloud, IEEE/ACM International Symposium on Cloud Computing (Cloud 2018), San Francisco, USA, July 2018.

[20] Thien, F., Beggs, P. J., Csutoros, D., Darvall, J., Hew, M., Davies, J. M., ... & Guest, C. (2018). The Melbourne epidemic thunderstorm asthma event 2016: an investigation of environmental triggers, effect on health services, and patient risk factors. *The Lancet Planetary Health*, *2*(6), e255-e263.