
An assessment of a new determinant for smarter route choice

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Abstract

The principle behind a route selection from a given set of the alternatives is to select a route that offers least cost. Along with many traditional cost factors of route choice (e.g. travel time, fuel cost, distance, transfers), different cost factors, like emission for identifying energy efficient, or the environmentally friendly route were applied in many studies recently. A similar attempt was conducted in this paper with an aim to identify healthier routes for smarter travel. From a health perspective, therefore it is necessary to select and estimate a new cost factor that is representative of the quality of the routes. The level of exposure to a particular pollutant, or dose could be one of the factors. Dose is the amount of pollutant that someone inhales during travel, and thus, it is a function of exposure concentration of a pollutant, travel time and breathing rate. A particular challenge is to estimate the exposure concentration of a pollutant along each road in a network, and thus, estimation of exposure concentration has been much focus of this paper. PM₁₀ was selected for this task as a generic pollutant.

A possible low cost, yet may be the most effective approach to estimation exposure concentration in a city scale is Land Use Regression (LUR) method. Fixed Site Monitoring (FSMs) PM₁₀ data (2007-2009) has been applied for developing LUR model where explanatory variables included traffic variables (e.g. Traffic volume, road length), land use and topographic information, weather, and demographic information. After LUR model development in a multivariate linear regression form, a neural network (NN), and a non-parametric regression were applied to obtain a best fit model, optimising the relationship between response and explanatory variables. The best fitting NN model was applied to estimate the exposure concentration in 1491 additional unmonitored locations in Dublin for two test days in 2009, and results were compared with actual measurements in a route. Later, an exposure concentration map was developed using kriging technique for a test day in 2009. PM₁₀ concentrations were then transferred to the road network level to estimate the exposure concentration along the roads. At last, dose was calculated based on the exposure concentration, travel time and breathing rate. Finally, the ArcGIS Network Analyst tool was deployed to assess the applicability of dose as a cost factor for route choice models. Shortest paths based on generalized cost, travel time, distance, CO₂ emission, and dose/exposure concentration at free-flow traffic condition outlined a limited scope of dose as a cost factor, or a component of the generalised cost.

1. Introduction

A primary target for route choice of the travellers is to minimise travel time, or travel cost. Route choice for the travellers may also be governed by many criteria, such as reliability, avoiding congestion, maximizing comfort, and optimizing fastest routes [1, 2, 3]. Since the last decade, CO₂ emission from vehicles has also been studied as a determinant for choice of routes. Some transport models [4,5], CO₂ as a component of the generalized travel cost factor [6], field trial and experiment using navigation systems [7, 8], etc. provided evidence that individuals may reduce carbon footprint choosing Eco-routes. Recently, intelligent transportation systems (ITS) based methods and devices for Eco-routing were discussed in many studies to facilitate the drivers' route choice decision-making process [9, 10]. Healthier routes based on the exposure to pollutant concentration can also be presented to the travellers through these ITS facilities, however the impact of that is yet known.

Thus, an attempt was conducted to assess the effects of a new cost factor that is a representative of the quality of the routes. Route level exposure studies [11,12] showed that different routes offered different level of PM_{2.5} concentration in the cities. Thus, routes with least PM concentration from the alternatives may be a healthier route. Here, in this paper PM₁₀ that primarily originate from traffic and domestic sources was selected as a generic pollutant because of its detrimental effect in Ireland and the EU, and availability of data. Exposure to PM₁₀ caused health effects on breathing and respiratory

systems, damage to lung tissue, cancer, and premature death [13]. Thus, from health perspective least exposure to PM₁₀ is desirable for travellers. However, as a reference [14] showed that Eco-routing did not necessarily reduce vehicle travel distance or travel time; thus, there may have such similar effects if PM₁₀ concentration will be chosen as a cost factor. In order to assess that effect, a particular challenge is to estimate the exposure concentration of PM₁₀ along each road in a network, and thus, estimation of PM₁₀ exposure concentration has been much focus of this paper. Finally, four cases were assessed that presented comparison of least PM₁₀ route with other routes based on conventional cost factors. The cost factors were estimated for a vehicle performing work trips in the Dublin road network.

2. Methodology

2.1 Landuse regression model

Many methodologies have been developed for exposure modelling in a citywide scale, however, the predictive performance of Landuse Regression (LUR) modelling has been shown to be no less than that of more complex alternatives [15,16]. LUR models utilise the monitored levels of the pollutant of interest as a dependent variable, and variables such as traffic, topography, and other geographic variables are considered as independent variables in a multivariate regression model [17]. The land use regression usually appears in the form of the Equation (1).

$$E = C_0 + A_1X_1 + A_2X_2 + A_3X_3 + \dots \dots \dots A_nX_n + \epsilon ; \dots \dots \dots (1)$$

Where, E = Exposure Concentration; X_1 = Traffic variable; X_2 = Land use variable ; X_3 = Weather variable; X_n = Other variable ; ϵ = Error ; A_i = regressing coefficient.

There are no methodological limitations for number monitoring sites [15], but the variability of exposure across various sites may be a factor important in ultimate model accuracy on a large spatial scale [17]. At the time of writing, the lowest number of monitoring stations as input into an LUR model reported in the literature was 11 [18]. Reference [19] reported that LUR model developed in 1999 produced similar results at-least in El Paso, USA in comparison to the models developed in 2006-2007. Thus, 2007-2009 PM₁₀ dataset has been considered for model building as additional monitors were available in this period. However, the inclusion of data over the years for LUR model development was not discussed in the literature yet. In total, the PM₁₀ concentration data was collected from seven local authority Fixed Site Monitors (FSMs) [20]. These seven sites were diverse in the nature; three sites were located in the city centre, two are near to the coast, and one in a park.

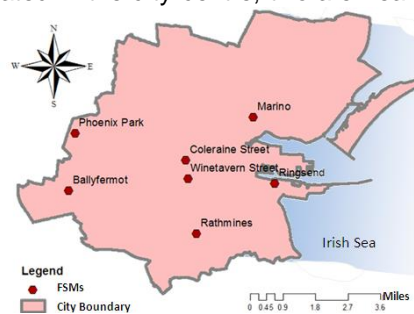


Figure 1: PM₁₀ monitoring stations Dublin

As regression assumes that data should follow a normal distribution, natural log transformation of pollutant concentrations was considered in the model. To avoid unrealistic prediction of the model and over fitting, illogically correlated variables were removed [18,19,21], and variables having at least .05 significance were retained. One independent variable from each type (e.g. road length) around FSMs was allowed to enter into the model in order to avoid multicollinearity [22]. Finally, the variables having a Variable Influential Factor less than 4 were selected for the model.

Several studies incorporated seasonal impact on the land use regression [22,23]. Reference [24] developed models considering the monthly impact, whereas [25] developed a LUR model with daily variation. The reported effective high resolution LUR model [25] included day of the year and the name of the day for model development. This may be useful for past data mining, but may not be suitable for future prediction. Besides, such high resolution models [24,25] were designed to meet research objective, rather improvement of model performance. Here, seasonal and daily variables were considered as a means of improving the LUR model. The first assumption is: average seasonal temperature and rainfall are differing for summer and winter that must have an impact on exposure

concentration as because higher rainfall reduces the PM₁₀ concentration in the air; on the other hand, people operate solid fuel heating appliances, which in turn may cause an increase in emitted PM₁₀ on cold days. It can also be assumed that the diurnal pattern of the primary pollutant source-traffic has an impact on exposure concentration.

As a further means of improving the explanatory power of the models, alternative modelling techniques were conducted. Weather variables are highly non-linear in nature and have complex interactions. Non-parametric regression and neural network may fit in this circumstance. Literature review showed that LUR in the form of MLR equation is popular, however, few studies also used different forms of non-parametric function in LUR equation, or applied non-parametric model [25,26]. Non-parametric regression in the form of locally weighted scatter plot smoothing (LOWESS) was applied here, whereas the Levenberg-Marquardt backpropagation technique was applied for NN model.

2.2 Independent variables

A number of independent variables that are representative of the physical properties were assessed (Table 1) for model development. In addition, weather variables were also included in the models. Weather variables have already been successfully integrated into LUR models in many previous studies [22,27]. Different buffer zones were established around each FSM, observing the literature, and values for each land use independent variable in buffer zones were determined using ArcGIS software.

The annual average daily traffic (AADT) surrounding each of the FSMs was determined for different sizes of buffer (100m – 350m, radius). The AADT data was obtained from the Dublin City Council (DCC) in GIS. On the other hand, hourly traffic at the nearest major junction was obtained from the loop detectors (SCATS). While the total traffic in a buffer may provide an indication of spatial variation of the average traffic, SCATS data may provide additional information about hourly and daily traffic variation in an area. Along with commonly used weather variables [28], a derived variable-Wind Index was assessed. Wind index has been calculated based on the following equation (2), adapted from [22]:

$$\phi = \frac{(1 - \cos(\phi - \theta))}{2} \dots\dots\dots (2)$$

Where, Wind index= ϕ ; ϕ = Euclidian direction (0–360°) from the nearest major road to monitoring site; θ = Wind direction in respect of true north.

Stability class was another derived variable from the weather data that was directly adapted from another study [28]. VKT, on the other hand, is a product of volume and road length. Roads above the tertiary category were classified as major road. Some land use layers of GIS landuse dataset for Dublin [29] were re-classified based on their spatial relationships with exposure concentration. These were: a) pollutant producing land use: Industrial and b) non pollution contributing land use: Open space. The altitude data was obtained from the [30], and population density of Dublin was collected from the [31].

Table 1: Independent variables for model

Category	Variable Name	Code	Pearson r	R ²	Selected
Traffic	Traffic at nearest major intersection**	D ₁	0.27	0.073	
	Traffic Volume* (100m)	D ₂	0.26	0.069	
	Traffic Volume* (350m)	D ₃	0.31	0.095	√
	Peak traffic at nearest intersection*	D ₄	0.26	0.068	
Landuse and topographic	Major Road ⁿ (200m)	D ₅	0.28	0.080	
	Major Road ⁿ (500m)	D ₆	0.29	0.084	
	Total Road ⁿ (200m)	D ₇	0.29	0.086	
	Total Road ⁿ (500m)	D ₈	0.34	0.114	
	Altitude* in meter (100m)	D ₉	-0.29	0.085	√
	Industrial Area (1000m)	D ₁₀	0.15	0.021	
Demographic	Open Space area (1000m)	D ₁₁	-0.29	0.086	
	Population density* (100m)	D ₁₂	0.25	0.064	
Weather	Temperature* (C)	D ₁₃	-0.28	0.080	
	Precipitation** (mm)	D ₁₄	-0.21	0.043	√
	Humidity* (%)	D ₁₅	-0.05	0.002	√
	Radiation* (W/m ²)	D ₁₆	-0.02	0.001	
	Wind speed* (m/s)	D ₁₇	-0.32	0.106	√
	Dew Point* (C)	D ₁₈	-0.31	0.096	√
Derived Variables	Stability Class	D ₂₀	0.28	0.078	√
	Wind Index	D ₁₉	-0.32	0.106	√
	Vehicle Kilometre Travelled-VKT (50m)	D ₂₁	0.21	0.045	

Note: D_i represents independent variables utilised for Dublin; Numerical values in brackets indicate the corresponding buffer size; all length/distance is in km and an area is in km²; * indicates daily average, or average, **indicates daily total, and ⁿ = length.

2.3 Route level estimation

The LUR model was developed based on the limited number of monitoring stations, and the model was applied to predict exposure for selected different points of interest in the city. Those point selections were based on a combination of random choice and real world data collection points in a route. Based on the semiveriogram, the appropriate kriging method was chosen for citywide extrapolation of PM₁₀ concentration and estimations have been transferred to the route level. Thus, dose value has been calculated based on the following equation (3).

$$D = \int_{t_1}^{t_2} C(t).IR(t,m).dt ; \quad \dots\dots\dots (3)$$

Here, D=dose (µg); IR(t,m)= Inhalation rate (m³/hr) based on mode; time in hour; and C(t)= µg/m³;

2.4 Network setup

The commonly applied cost components for route choice, such as generalized cost, travel time, distance, and CO₂ emission were estimated based on the information below (Table 2). Initially, speed limit for each road in the ArcGIS road map has been updated by Speed Limit By Laws, 2011 of the DCC. Thus, speeds have been estimated from the [32] for these speed limits, and ArcGIS network database has been updated accordingly. Estimated speeds were considered as a free flow speed. For CO₂ emission and other network attribute, a Euro III emission standard petrol powered vehicle (Y) has been chosen. It has been assumed that that vehicle conducted work trips with 1.31 occupancies. The required cost attributes were determined using the following equations (4,5). As no comparison was made against public transport or considering parking fare policy, the generalized travel cost (GC_i) was estimated considering only in-vehicle time and vehicle running cost.

$$GC_i = VOT * TT_i + C_i * L_i \quad \dots\dots\dots (4)$$

Where, GC_i = generalized travel cost on the link i; VOT= Value of time of the travellers; TT_i= travel time on the link i ; C_i= running cost of a vehicle on the link i, and L_i= length of the link i.

$$E_i = EF_i * L_i \quad \dots\dots\dots (5)$$

Where, E_i = average CO₂ emission on the link i; EF_i= vehicle emission factor on the link i using the emission factor equation in Table 2 for free flow speed ; L_i= length of the link i.

Table 2: Network setup for test cases

Attribute	Details	Value	Reference
Average link speed	Urban national -50km/h sign	60km/hr	[32]
	Urban arterial – 60km/h speed limit zone	68km/hr	
	Urban arterial – 50km/h speed limit zone	57km/hr	
	Urban residential – 50km/h zone	29km/hr	
	Urban arterial – 60km/h speed limit	80km/hr	
Vehicle model, Y	Euro III; Petrol Engine (1400-2000cc); <2.5 GVW*	----	----
Emission factor for Y	(2532.4+118.34x-0.43167x ² +0.0066776x ³)/x **	g/km	[33]
CO ₂ band for Y	Average emission 179g/km	E	
Running cost for Y	Petrol, Oil, Tyres, Servicing, Repairs & Replacement	.30 €/km***	[34]
Trip type	Work trip	----	----
Average occupancy	Car driver & passenger	1.31	[35]
Value of time		0.46 €/Min [^]	
Inhalation factor		0.57 m ³ /hr	

*Gross Vehicle Weight; **x= speed (range:5-140km/hr); *** Cost Per Km was based on 16,000VKT; ^= per person

3. Results

The analysis was performed in R – statistical software, XLSTAT, Arcgis, SPSS and MATLAB.

3.1 LUR result

To develop models in Table 3, the complete procedure described in section 2.1 was followed. The base model is a standard LUR model whereas, Final LUR model includes dummy variables, termed as winter and days of the week. While '0' is the value for this variable, the model predicts the PM₁₀ concentration for the summer season; using '1' allows a coefficient of 0.2391 to add to the equation which increases the predicted value for winter. Similarly, coefficient for Monday in Final LUR equation means, prediction will be done for Mondays while all the coefficients of the days in the equation are zero. Finally, a normality test for the Final Model was conducted that confirmed an unbiased and homoscedastic relationship between residual and fitted values.

Table 3: PM₁₀ Panel Data Models for Dublin

Model	Variables have less than or equal to .05 Significance	R ²	P	SE
Base model	$\ln Y = 2.312 + 2.322E^{-07}D_3 - 4.654E^{-05}D_9 - 9.004E^{-05}D_{14} - 4.026E^{-05}D_{15} - 7.715E^{-02}D_{17} - 4.186E^{-02}D_{18} + 6.975E^{-02}D_{19} + 3.225E^{-01}D_{20}$	0.37	<2.2e-16	0.43
Final LUR	$\ln Y = 2.368 + 2.359E^{-07}D_3 - 4.465E^{-05}D_9 - 6.509E^{-05}D_{14} - 7.402E^{-05}D_{15} - 8.380E^{-02}D_{17} - 2.717E^{-02}D_{18} + 8.199E^{-02}D_{19} + 2.997E^{-01}D_{20} + 2.391E^{-01}\text{Winter} + 8.658E^{-02}\text{Tuesday} + 1.112E^{-01}\text{Wednesday} + 1.401E^{-01}\text{Thursday} + 1.213E^{-01}\text{Friday} + 3.955E^{-02}\text{Saturday} - 8.788E^{-02}\text{Sunday}$	0.42	<2.2e-16	0.42

*Significance level is .1

NPR was deployed for Final LUR (Figure 2a). The LOWESS method combines multiple regression models in a *k*-nearest-neighbour-based meta-model. To define the structure of the model, smoothing parameter value- *k* nearest neighbours: % = 50, and the degree of the local polynomial as 1 were defined. Tricube weight function was used as the kernel function. The Final LUR equation was also optimised using neural networks (Figure 2b). After several iterations with different number of hidden neurons (10, 25, 30, 40, 50, and 60), the best performing network architecture was selected. The combination for “input-hidden layers – output” for Dublin (18-30-1-1) yielded consistent satisfactory results. The results were included in Table 4.

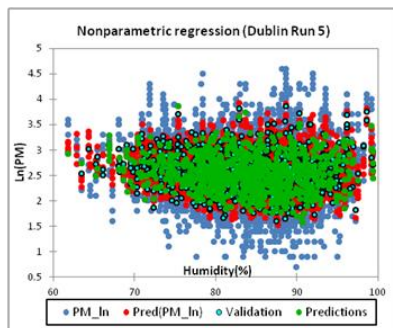
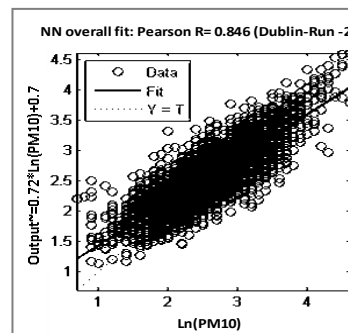


Figure 2: a. Non-parametric test ;



b. Neural Network for Dublin

3.2 Validation

For model validation common approaches were either leaving one monitoring station out of model development and carry out the cross validation for (n-1) times, or sub-dividing the monitoring sites into a training data set for model development and deploying the rest of sites for model validation [15], or leaving a certain percent of the data for validation and establish the model using the rest of the data.

Table 4: Validation of models

Stage		LUR*	NPR	NN	Stage		LUR*	NPR	NN		
Full Model	R ²	0.42	0.48	---	3	r'	0.66	0.72	0.82(.76)*		
	MSE	---	0.16	---		R ²	0.43	0.53	---		
1	Partial Model	r'	---	---	0.82	Validation	MSE	0.18	0.16	0.11(.13)*	
		R ²	0.41	0.48	---		r'	---	---	0.83	
	Validation	MSE	---	0.16	0.096	Partial Model	R ²	0.4	0.48	---	
		r'	0.65	0.7	0.79(.79)*		MSE	---	0.16	0.093	
		R ²	0.42	0.49	---	Validation	r'	0.7	0.72	0.79(.76)*	
		MSE	0.16	0.14	0.10(.14)*		R ²	0.45	0.52	---	
2	Partial Model	r'	---	---	0.85	Validation	MSE	0.16	0.14	0.11(.12)*	
		R ²	0.41	0.48	---		r'	---	---	0.82	
	Validation	MSE	---	0.15	0.08	Partial Model	R ²	0.41	0.47	---	
		r'	0.63	0.69	0.81(.80)*		MSE	---	0.15	0.099	
		R ²	0.4	0.48	---	Validation	r'	0.63	0.69	0.74(.79)*	
		MSE	0.18	0.16	0.10(.11)*		R ²	0.4	0.48	---	
3	Partial Model	r'	---	---	0.84	5	Validation	MSE	0.17	0.15	0.13(.13)*
		R ²	0.41	0.47	---			r' = Pearson correlation; * values in bracket illustrates results from testing using 5% observation, and value outside of the bracket depicts the result of validation with 10% observation.			
		MSE	---	0.16	0.084						

*Final LUR

Having a limitation of the number of routine monitoring sites available, only the latter approach was suitable in this context. In order to avoid losing information, observations for model development and validation were conducted with complete and segmented datasets separately. For the validation purpose, 85% observation from the original dataset was separated randomly five times using SPSS

software (Runs 1-5). The Final LUR and Non-parametric models were developed using the 85% datasets. These partial models (not all the variables were highly significant as original models) were applied to estimate PM₁₀ for the rest of the 15% observation. The predicted concentrations were compared against the actual measured concentrations, and performance measure (e.g. R²) has been derived for all five runs. All the MLR validation R² were around 41% for LUR Model. NPR provided improved results, however, NN model was found to be consistently yielded better results. This optimized NN model has been applied for further analysis.

3.3 Route level extrapolation

NN was applied to estimate PM₁₀ concentration in 1491 unmonitored locations, and thus no spatial auto-correlation was tested as results would be meaningless. The model has been compared with the data from PLAM Project [37] for two days in summer and winter. The field data were collected by Milton Aerocet 531 portable exposure monitoring device (PEMD) along with a GPS device carried by a traveller. The data were Geo-referenced and imported to Arcgis for analysis. The resolution of PEMD data is 2 minutes, whereas the developed model is for daily average, and thus, the local variation in the modelled data was not expected to be matched with actual measurement (Figure 3). However, the average is satisfactory. Finally, for citywide extrapolation ordinary kriging method and circular semivariogram were selected for a day in winter (16.06.09), and the result at the road level has been shown (Figure 4).

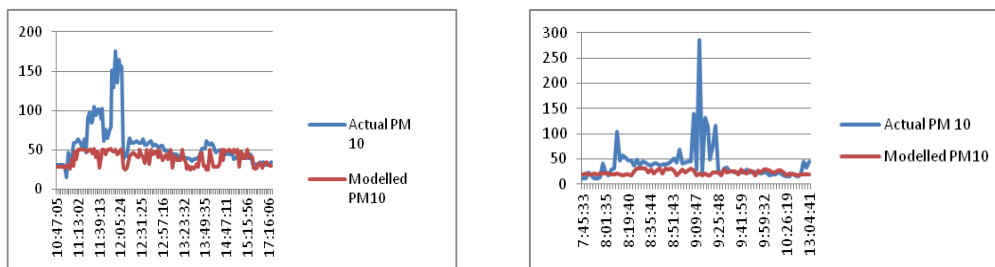


Figure 3: Actual vs. modelled data (a. 16.04.09 data on left & b. 26.06.09 data on right)

The data in Figure 3 (a, b) was collected on a route shown as case 3 (Figure 5). In summer (26-06-09), the modelled average value on the route was 23.08 µg/m³ whereas the actual average was 40.10 µg/m³. In winter (16-04-09), modelled and actual values were 39.74 and 56.21 µg/m³ respectively. The higher winter value and lower summer value were contradictory with some studies [12,38] where summer values were found higher than that of winter values in the transport microenvironment. This may be because of meteorological condition as the average concentration in monitoring stations in Dublin also higher in Winter (Summer & Winter average were 10.94 & 16.27 µg/m³ respectively).

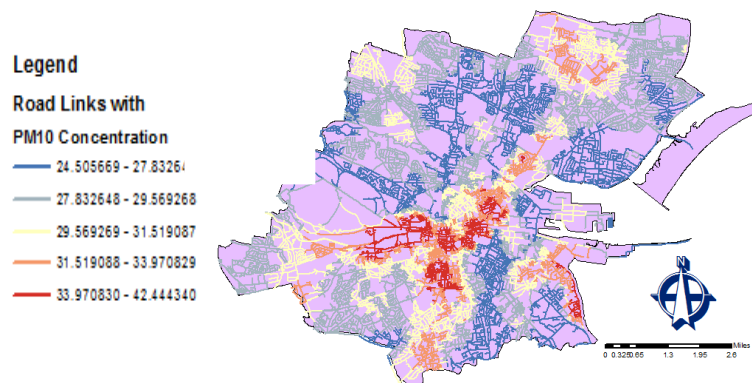


Figure 4: Exposure concentration in Dublin road network (16.04.09)

3.4 Cost factor assessment

The basic assumption for traffic assignment stage of the transport modelling are that the individual will have complete information, and identical perception of cost as well as the individual will follow the same route choice criteria, and will try to minimize the cost. Thus, the driver of the work trip maker in the test cases were considered to minimize either the travel cost, distance, travel time, CO₂, or exposure to PM₁₀ dose. Four cases have been considered and routes in terms of least PM₁₀ dose and other attributes have been presented in the following Figure 5. Each origin and destination points were displayed as O_i & D_i. Shortest path tool of Arcgis network analyst has been deployed for analysis.

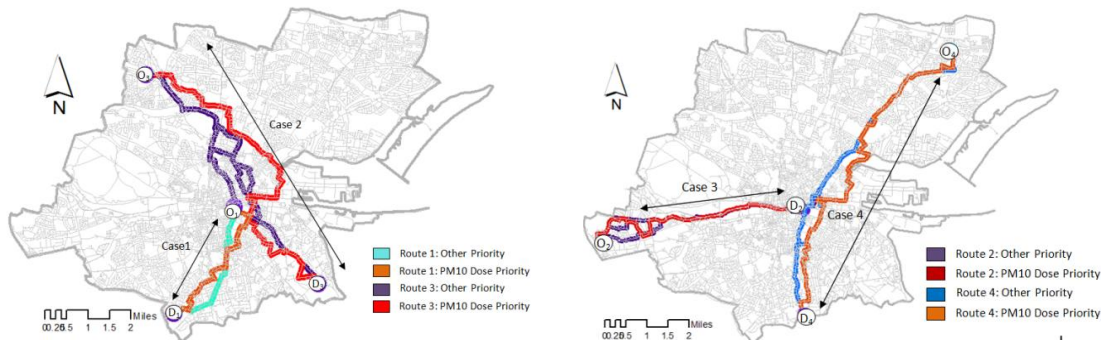


Figure 5: Least PM₁₀ routes in comparison to other attributes

4. Discussion and conclusion

The final LUR model in this study did not yield high explanatory power, however the experiments with alternative models yielded some good fit with the data. An important finding is that the limited number of sites with less spatial coverage can be offset by using data from additional sites if available in longer periods. Besides, seasonal and daily variation can be added to increase model's performance. Thus, this study provided evidence that data from limited routine monitoring station can also be applied for the LUR methodology.

In route level, the actual dose while travelling may differ from the average dose as may be observed from the Figure 3. The dose may increase as a result of travelling while pollution level is higher, or an increase in travel time due to congestion. This latter case is also true for an increase of CO₂, and cost. Thus, the following discussion has been drawn from average attribute values in free flow speed condition, however the findings should stand for all traffic conditions. Figure 5 showed that the least PM₁₀ routes are different from all other routes. All the routes based on the least value of the conventional attributes overlapped with each other for the cases 1 and 4. Least cost routes other than based on PM₁₀ did not overlap with each other in the cases of 2 and 3, however showed similarities. It has been observed in all the cases that least PM₁₀ routes included unnecessary turns and roads between the origin and destination where the PM₁₀ concentration was lower.

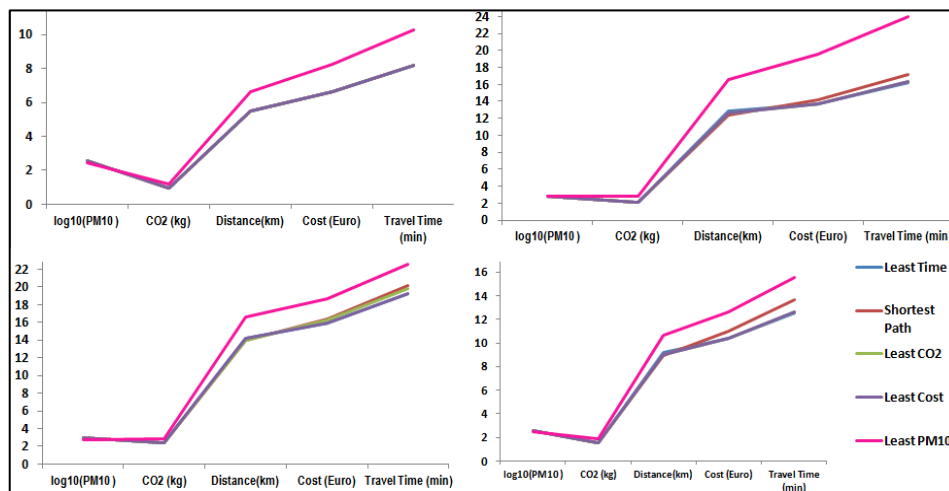


Figure 6: Least PM₁₀ dose (μg) in comparison to other attributes (top left: case 1 and the cases (2-4) were presented clockwise)

The Figure 6 provided a detailed insight about the cases. PM₁₀ dose was presented in log₁₀ of Pico - grams of dose for simplification of the figure. On an average, the reduction of dose .0004-. 0013 μg , the distance, CO₂ travel time and generalised cost have been significantly increased. This is because of the characteristics of the unit value of the conventional cost components. The unit values are not area specific, and primarily depend on the vehicle trajectory, whereas dose value is highly dependent on local pollutant sources, like households and traffic intensity on the roadway along with vehicle trajectory.

Reference [39] concluded that only 3% Irish people considered CO₂ emission in their route choice. The majority of people (55%) primarily focused on travel time with a successive attention to CO₂. Thus, dose factor may have a little scope to be considered as a route choice factor, or a component of the generalised cost considering the findings above.

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