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Research Article

Integration of Traffic Management and an Artificial Intelligence to Evaluate Urban Air Quality

Mohammad K. Younes*, **Ghassan Sulaiman**[1)], **Ali Al-Mashni**[2)]

Department of Civil Engineering, Philadelphia University, P.O. Box 19392, Amman, Jordan
[1)]Department of Civil Engineering, Aqaba University of Technology, P.O. Box 11947, Aqaba, Jordan
[2)]Monotoring and Assessment Directorate, Ministry of Environment, P.O. Box 1408, Amman11941, Jordan

***Corresponding author.**
Tel: 00962 6 4799040
Email: myounes@philadelphia.edu.jo

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ABSTRACT Emissions from motor vehicles are the primary source of air pollution, especially in congested urban centres. However, through effective traffic management, it has been found that the level of pollution can be significantly reduced, facilitating the mobility of urban arterials. This study aims to quantify the extent of traffic emissions and to identify the influence of traffic management to improve air quality and reducing traffic emissions. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed to estimate the extent of traffic emissions (NO_2 and PM_{10}) at certain intersections. Then, a traffic management simulation software was also used to simulate traffic and to build a traffic improvement scenario at these intersections. This was followed by measuring the improvement in air quality due to traffic management modification, analysed using the developed ANFIS model. The results showed that reducing the delay at certain intersections may reduce NO_2 and PM_{10} significantly. The proposed hybrid model increased the forecasting accuracy and improved the perception between the relationship between traffic characteristics and pollutant emissions. Additionally, it facilitates the work of city planners and helps decision making regarding urban air quality.

KEY WORDS Traffic management, Air pollution, Vehicle emissions, Air quality index, ANFIS

1. INTRODUCTION

Pollutants from motor vehicle emissions represent a significant problem globally in developed and developing countries and act as one of the main sources of air pollution in urban centres via transportation (Giles-Corti *et al.*, 2016). For instance, traffic related emissions are responsible at least for 50% of Particulate Matter (PM) (Wui *et al.*, 2018) as well as it is main source of NO_2 in urban areas (Agudelo-Castañeda *et al.*, 2020). However, quantifying the extent of the problem will undoubtedly attract the attention of decision-makers to focus on resolving this issue (Sallis *et al.*, 2016). Air quality in many cities has received unprecedented attention over the last decade, due to its capacity to degrade air quality in these cities (Gong *et al.*, 2017).Vehicle traffic emissions have been recognised as a series of complex events (Guan *et al.*, 2016), involving the interaction and contribution of three major factors, namely weather conditions, vehicle and road characteristics (Pinto *et al.*, 2019).

Recently, many studies have been conducted to understand and identify the factors that contribute to air pollution and emissions. For instance, the relationship between traffic variables and PM was investigated by Guoyuan Wu (Wu *et al.*, 2017), where they applied real-time traffic data to estimate the PM_{10} concentration and distribution. Furthermore, the integration of VISSIM, a traffic simulation software, with emission model was implemented to improve transportation emission modelling (Abou-Senna *et al.*, 2013). In another study, various roads in Paris city have been assessed to quantify the emission factors and to investigate the reasons of PM concentration variations of the roads (Amato *et al.*, 2016). While Mayer *et al.* evaluated air quality in vehicle cabins during traffic congestion finding that the concentration of pollutants inside the cabin could reach significantly high levels, up to ten times more than the concentration of the pollutants outside the cabin (Mayer *et al.*, 2018). Similarly, an integrated model used to simulate traffic emissions was developed in a medium-sized city in France. Here, a 3D mesoscopic traffic simulation model used to collect and measure metrological and air quality from local authorities, thereafter, NO_2 and PM_{10} emissions were simulated via regression analysis (Mihăiță *et al.*, 2019). However, applying traffic management strategies which are summarized by Redesign of Traffic Signal (RoTS) and Cycle Time Optimization (CTO) improves the intersection performance. Consequently, the amounts of traffic emissions will be reduced.

1.1 Redesign of Traffic Signal Phases (traffic signal cycle time is fixed)

Efficient traffic signal control, to improve safety and mobility, is a significant issue among the traffic community. For instance, signal time is optimised to minimise expected vehicle delays simultaneously, and consequently reduce the emissions from traffic causing pollutants (Han *et al.*, 2016). The majority of traffic signals are of a fixed type, leading to continuous time distribution of the signal phases. However, a shift or any change in the flow of traffic or time may occur due to various activities. For instance, a new construction or transportation project may lead to a change in traffic flow, direction and consequently affecting travelling time. Moreover, it may lead to alterations in traffic flow in each direction which necessitates a periodic traffic survey and consequential revision to examine required traffic volume changes in each direction at the road intersection. Regarding the dependence on knowing actual updated traffic volumes, the required time adjustments of light signals can then be estimated to enhance the movement of traffic.

Consequently, this study aims to analyse and evaluate air quality improvement resulting from the management of traffic at urban intersections. In achieving this aim, a model is developed to predict traffic emissions (NO_2 and PM_{10}) at specified locations using factors such as weather conditions and traffic characteristics. Further, the model optimises the cycle time and manages traffic at the targeted intersections to minimise the level of congestion. The developed emission model and improved traffic characteristics are used to then model and evaluate the anticipated reduction of emissions due to traffic improvement. The remainder of this study is organised as follows: Section 2 presents the study area, data and provides an overview of the model employed in this study. Section 3 highlights the model's outputs and the impact of traffic management in minimising vehicle emissions. Lastly, in Section 4, the overall conclusions are presented.

2. METHODOLOGY

2.1 Data Collection and Study Area

The collected data were grouped into three categories, namely traffic characteristics, weather and emissions, as displayed in Table 1. Data related to the weather and gas emissions were collected from the Ministry of Environment (MoE) including temperature, humidity, wind speed, concentrations of NO_2, and particulate matter (PM_{10}). However, the collected emission are within the Jordanian limits, that is 120 μg/m^3 for PM_{10} and 80 ppb for NO_2, for all locations expect for TAB. Traffic characteristics and analysis were carried out during a normal weekday and at peak hours of selected locations. The data were collected via field observations, with physical/manual counts taken at both signalised and un-signalled intersections. Traffic characteristics included delay, that represents the whole intersection but not a single leg (seconds/vehicle), traffic Queue Length (QLEN) in metres and Volume to Capacity ratio (V/C)%, However, appendix 1 briefly defines these terms, The rush/peak hours were between 7 am and 9 am and between 2 pm and 4 pm, which represented the school and business times in Jordan. The traffic emis-

Table 1. Collected and analysed data.

Site	Traffic characteristics				Weather characteristics			Emissions	
	Delay (Sec/vehicle)	V/C (%)	QLEN (m)	Volume (vehicle/hr)	Temp (C°)	Hum (%)	wind speed (km/hr)	NO_2 (ppb)	PM_{10} (ppb)
KHG	47.8	89.8	25.3	2,918	22.5	42.3	7.0	3.8	38.5
UNI	18.5	78	9.8	6,686	22.0	42.7	7.2	13.7	70.5
TAB	77.4	95	34	8,369	22.5	43.0	6.2	21.1	169.1
YAR	120.7	123	55.9	5,937	23.8	45.7	5.0	10.6	25.8
BAR	45.8	79.6	17.6	1,593	18.9	21.3	4.6	26.1	36.7
HAS	150.2	154	53	4,887	19.4	22.0	4.6	4.5	106.6
HAJ	109.5	109	38	2,808	20.8	48.7	7.6	17.7	116.8
HH	85	84.4	43.5	3,140	21.9	44.0	8.1	15.4	113

sions and traffic characteristics were collected during the same period at each site. The peak hour calculation was undertaken to determine the design representing hourly traffic volume.

The targeted sites were considered as 'hot spot' locations, near to main roads signifying congestion points in the cities of Amman, Irbid and Zarqa, given they are the main populated cities in Jordan, as shown in Fig. 1. These sites were also suggested by the MoE, representing environmental hot spots for traffic and the emission of air pollutant. For instance, the site named TAB is an intersection situated near the north bus station in Amman, which links Amman with the city of Zarqa. It is also considered as one of the busiest roads in the country that links the central and northern regions. BAR is an intersection located in the central area of Irbid city and lies within the commercial centre of the city. KHG and UNI are both main roads in Amman having high traffic volumes, which connect Amman with neighbouring cities and districts. YAR is in the city of Amman within the light industry zone, and HH is the main road in the city of Zarqa connecting Zarqa with Amman. Moreover, it represents one of the main commercial streets in the city of Zarqa. HAS represents the entrance to the city of Irbid close to the bus station, signified as a sports city, while HAJ is a residential area in the city of Zarqa.

Air emission modelling and data analysis were performed using MATLAB (7.14), and VISSIM micro simulation software was used to evaluate the intersection performance which optimised the cycle time for signalised intersections to decrease traffic delay at these intersections. In determining the efficiency of cycle time optimisation, intersection performance both before and after optimisation was tested independently regarding average traffic delay, average queuing length and volume to capacity ratio (V/C) (Sun *et al.*, 2013).

In the VISSIM simulation model, calibration was undertaken to test the validity of the model for the observed data. Here, during the model calibration process, the parameters were altered until achieving a qualitative and quantitative balance between the simulation and the observation. Usually, calibration requires several runs based on engineering judgement and experience. In this study, calibration of (Origin-Destination) OD estimation was applied. Furthermore, the collected data were verified, employing the GEH method, which is widely adopted for a variety of analytical purposes in traffic engineering, traffic forecasting, and traffic modelling. The formula for the GEH statistics is expressed below:

$$GEH = \sqrt[2]{\frac{(VOL_{obs}-VOL_{sim})^2}{(Vol_{obs}-VOL_{sim})/_2}} \quad (1)$$

where VOL_{obs} and VOL_{sim} represent the observed and simulated traffic volume, respectively.

For traffic modelling in the "baseline" scenario, a GEH of less than 5.0 would be considered as a good match between the modelled and observed volumes, and 85% of the volumes in the traffic model should have a GEH less than 5.0 (Chu *et al.*, 2011). However, given the obtained GEH value (GEH = 2.8) was less than the limit value, the developed simulation model was representative. Indeed, the number of runs could not be generalised to all existing intersections.

Fig. 1. Satellite views of the evaluated intersections.

2.2 Development of the ANFIS Model

ANFIS is a multilayer feed-forward network and performs a fuzzy logic function on incoming signals. To build the fuzzy logic structure, it is essential to (i) select the model inputs, (ii) determine the membership functions (MF), and (iii) generate the fuzzy rules (Sulaiman and Younes, 2018). The accuracy of the model's performance was evaluated using Root Mean Square Error (RMSE) (Antanasijević *et al.*, 2013; Willmott and Matsuura, 2005), shown by the expression below.

Table 2. Summary of the performance of various membership functions for PM_{10} and NO_2.

Code	Function description	PM_{10}		NO_2	
		$RMSE_{train}$	$RMSE_{test}$	$RMSE_{train}$	$RMSE_{test}$
Trimf	Triangular MF	0.42	84.88	0.51	11.61
trapmf	Trapezoidal MF	0.23	86.25	0.32	11.86
gbellmf	Generalised bell curve MF	0.61	84.2	0.767	11.56
gaussmf	Gaussian curve MF	0.69	84.01	0.78	11.57
gauss2mf	Two-sided Gaussian MF	0.20	86.23	0.283	11.81
pimf	Pi-shaped curve MF	0.16	86.25	0.242[b]	11.81[b]
dsigmf	Composed of the difference between two sigmoidal MF	0.19[a]	67.96[a]	0.275	12.71
psigmf	Product of two sigmoid MF	0.19	86.24	0.276	11.83

[a,b] The best MF performance for PM_{10}; [b] the best performance of the MF for NO

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(X_t - X_o)^2}{n}} \quad (2)$$

Where X_t is the actual output, X_o is the predicted output, and n is the number of outputs. The concept behind ANFIS modelling is to define the relationship between the inputs and output. Thus, the shape of the MF is updated and modified in order to mimic this relation and minimise the error during the training phase. This phase is repeated many times (epochs) until the desired convergence is acquired, at the minimum difference (error) between actual output and the ANFIS model output. For a first-order Sugeno fuzzy model, a common set of two fuzzy rules and a set of if-then rules are described as follows:

Rule 1:

$$\textit{If } x \textit{ is } A_1 \textit{ and } y \textit{ is } B_1 \quad \textit{THEN } f_1 = p_1 x + q_1 y + r_1 \quad (3)$$

Rule 2:

$$\textit{If } x \textit{ is } A_2 \textit{ and } y \textit{ is } B_2 \quad \textit{THEN } f_2 = p_2 x + q_2 y + r_2 \quad (4)$$

where A_i or B_j is a linguistic label (grade), such as "low" or "less", and p_1, q_1, p_2, q_2 are the design parameters determined by the system developer (Younes *et al.*, 2016). MF is a parameterised function in which any changes in the corresponding parameters produce a change in the function shape. The selection of the MF type is usually performed based on system demand, simplicity, speed and convenience, where its value should fall between 0 and 1 (Pramanik and Panda, 2009).

In this study, to minimize the modelling errors, the final structure of the ANFIS model was modified using several steps. First, the type of MF's was altered to determine the best function type for both NO_2 and PM_{10} emissions and then the number of MFs that minimises the RMSE (Lin *et al.*, 2013; Khatibinia *et al.*, 2012) was checked and selected for both pollutants.

3. RESULTS AND DISCUSSION

3.1 ANFIS Model Structure Development

Initially, the data, as shown in Table 1 were used to develop the preliminary ANFIS models. Here, traffic and weather characteristics were used as an input, while NO_2 and PM_{10} were used as an output, respectively. Additionally, odd inputs were used for training, while even inputs were used for testing. The developed preliminary ANFIS model was achieved using six inputs, single output, three MF's, five epochs and a hybrid training function. Next, to finalise the ANFIS model and update its structure, the optimum membership type was determined using three MF's, five epochs and by altering the MF types as shown in Table 2 to minimise the RMSE. The results, as shown in the table, indicate that the pi-shaped curve MF is the best function to represent the NO_2 emission, with $RMSE_{training} = 0.242$ and $RMSE_{testing} = 11.81$, while the best MF for modelling PM_{10} represents the difference between two sigmoidal MF; 0.19 and 67.96 for $RMSE_{training}$ and $RMSE_{testing}$, respectively.

In finalising the ANFIS structure, the number representing MF was optimised using the obtained best MF types to model NO_2 and PM_{10}, that are represented in a pi-shaped curve and representing the difference of the

sigmoidal MF's, respectively. The MF number was altered from 2 to 4. In addition, the optimum number of membership functions was selected based on the generated smallest RMSE for the training and testing phases. Table 3 presents the model's performance with a different MF number. The results indicate that using two MF's will reduce the RMSE for NO_2 modelling, and minimises the testing of RMSE by about 45% and the training RMSE by around 6%. However, the relatively higher testing errors may be attributed to limited model input readings, which can be avoided by increasing the number of readings. Moreover, PM_{10} emission sources in urban areas varied (traffic, natural, domestic, etc.) (Wang *et al.*, 2015). As such, the error potential was relatively higher in comparison to modelling NO_2. However, the optimum model for NO_2 simulation is two pi shape MF, while for PM_{10} modelling the optimum model is three MF of the type of difference between two sigmoidal functions.

Table 3. Performance summary of the various number of MF for PM_{10} and NO_2.

No of function	PM_{10}		NO_2	
	$RMSE_{train}$	$RMSE_{test}$	$RMSE_{train}$	$RMSE_{test}$
2	0.6	72.85	0.214[b]	6.5[b]
3	0.19[a]	67.96[a]	0.242	11.81
4	1.1	76.8	0.835	11.86

[a,b] The best function number

3.2 Cycle Time Optimisation by VISSIM

Cycle time optimisation for signalised intersections was undertaken using the VISSIM model which was carried out based on various traffic parameters such as vehicle type, % of heavy trucks, reduced speed area (speed limits) in the Central Business District (CBD), slope and effects of road parking. However, signal timing optimisation was the most efficient tool to improve mobility within the urban transportation system. Moreover, it enhances human life by reducing pollution emission, reduces congestion and saves both time and money for residents in urban centres (Park and Schneeberger, 2003).

During time cycle optimisation, both signal phases and total time cycle were alternately changed in the VISSIM software. Figs. 2, 3 show the optimisation of the cycle time from 65 sec in Fig. 2 to 80 sec in Fig. 3. Consequently, the phase time of signal group one increased from 19 sec before optimisation to 30 sec, leading to a reduction in traffic delay by 15% and this reduction will invariably help to reduce both noise pollution and emissions.

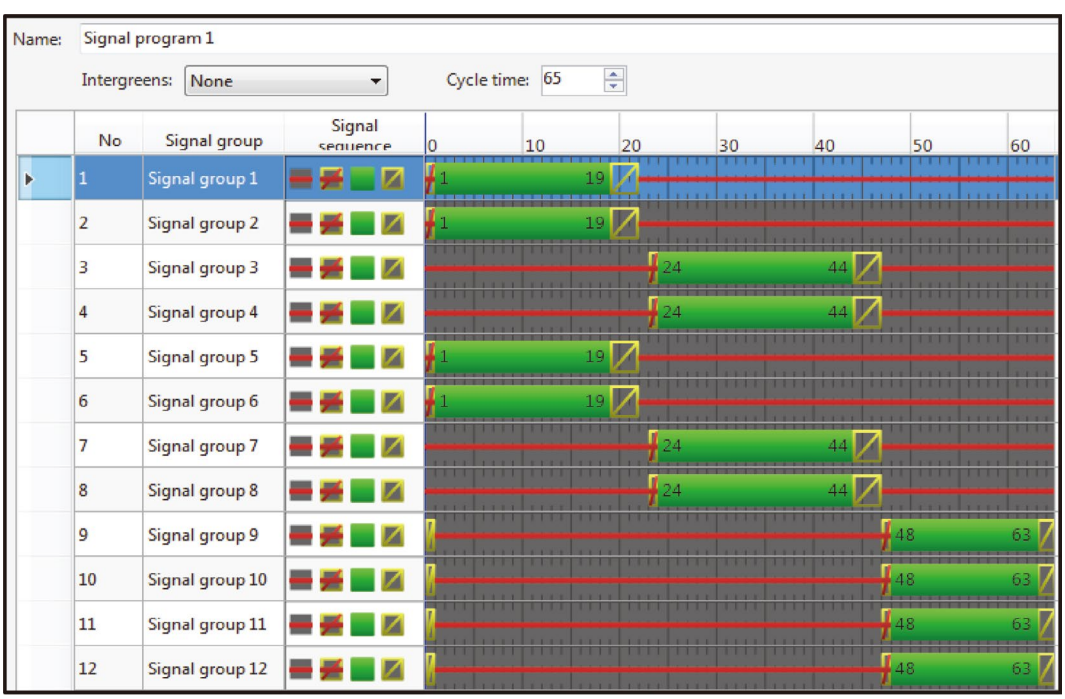

Fig. 2. Cycle time optimisation; cycle time 65 sec.

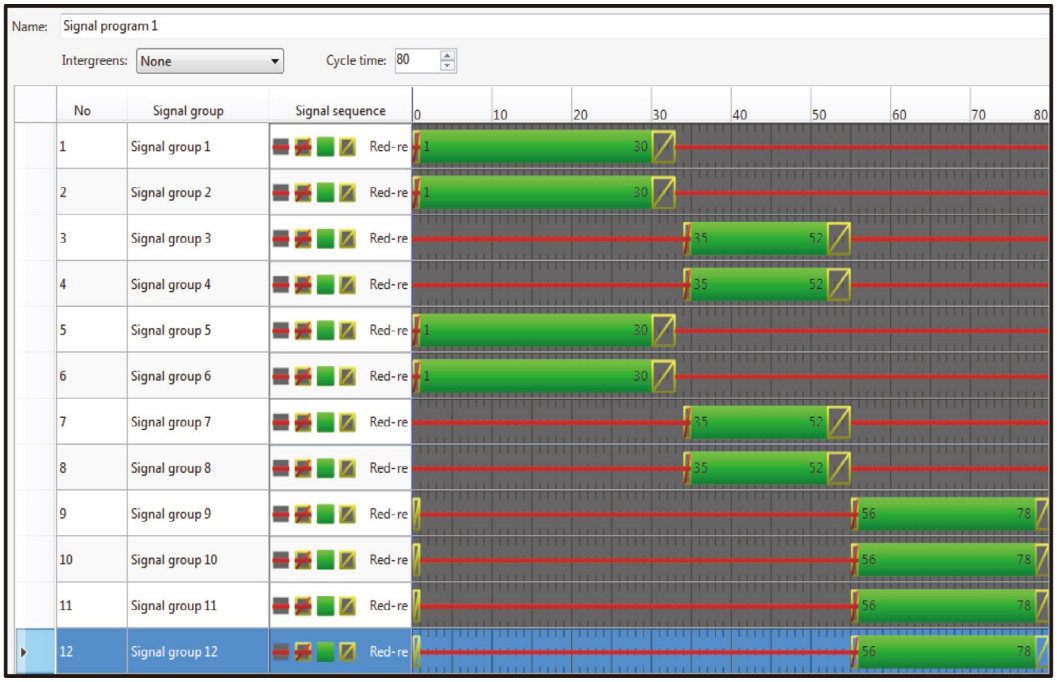

Fig. 3. Cycle time optimisation; cycle time 80 sec.

Table 4. Intersections performance results due to the improvements.

#	Intersection site	Before			After		
		Delay	V/C	QLEN	Delay	V/C	QLEN
1	KHG	47.8	89.8	25.3	30.4	82.3	19.8
2	UNI	18.5	78	9.8	11.8	73	5.6
3	TAB	77.4	95	34	69	89.3	29.3
4	YAR	120.7	123	55.9	95	105	44.3
5	BAR	45.8	79.6	17.6	39.6	71.6	12.8
6	HAS	150.2	154	53	127.6	143.3	36
7	HAJ	109.5	109	38	93	103	18.6
8	HH	85	84.4	43.5	79	77.6	29.8

3.3 Traffic management and geometric improvements

Traffic management includes the prevention of parking at a close distance upstream of an intersection, whereas on-street parking manoeuvres can often reduce the level of service, leading to additional delays and traffic congestion and emissions [3]. Thus, it is advisable to prevent heavy vehicles from using intersections during peak periods which would lead towards improving mobility within the urban transportation network. The results of applying these two techniques are presented in Table 4 below. As shown in the table, there is an improvement in reducing delays at all locations of between 7 and 36% and the length of vehicle queues decreased between 14 and 51%. The largest reduction was in HAJ. This is because the HAJ intersection is located within the residential area, where the streets are occupied with passenger cars being parked. Thus, preventing parking at the intersections of roads like these had a significant impact on performance. The lowest reduction in Q-length was in TAB because at such intersections the availability of parking spaces is limited, given its occurrence on arterial roads. Therefore, the difference before and after the development of traffic was relatively low.

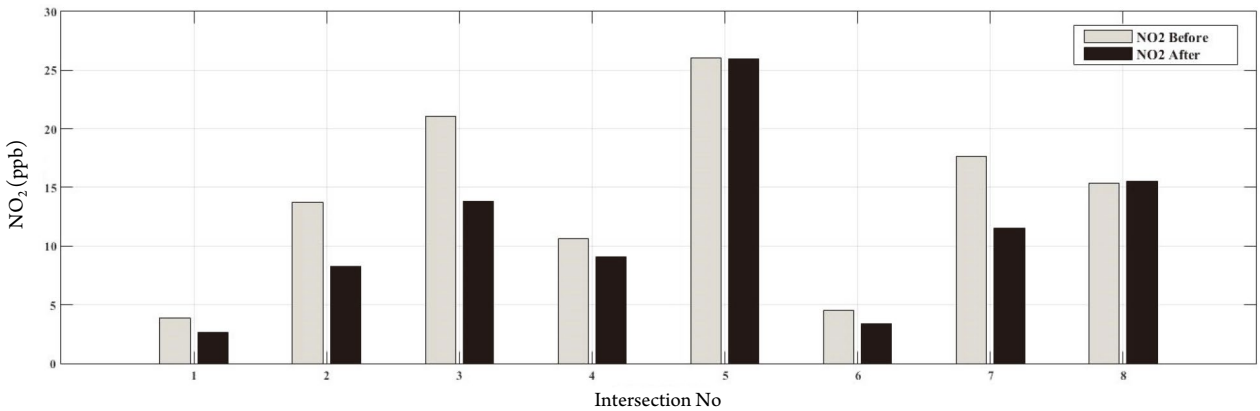

Fig. 4. Comparison of NO_2 emissions before and after traffic management.

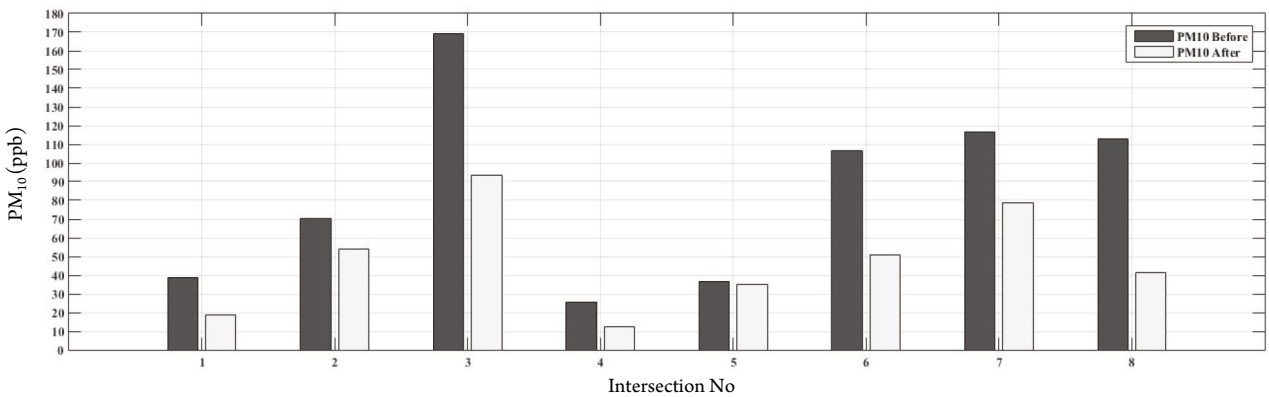

Fig. 5. Comparison of PM_{10} emissions before and after traffic management.

3.4 Evaluation of Air qQuality Improvement due to Traffic Management

The developed model and modified traffic characteristics were used to evaluate the reduction of expected emissions due to traffic management. As shown in Fig. 4 the largest reduction in NO_2 emission was expected at the UNI intersection, followed by the TAB intersection, having a percentage of reduction of between 39 and 35%, respectively. The UNI intersection is a hub highway at the capital city of Amman that links the central cities in Jordan (Amman, Zarqa and Salt). Furthermore, it is one of the most congested streets in the country, as it includes many commercial institutions. Thus, the enhancement of traffic congestion will significantly reduce traffic emissions. On the other hand, facilitating traffic movement at the TAB intersection will significantly reduce delays and minimise NO_2 emissions.

Fig. 5 presents the expected PM_{10} emissions due to the optimization of traffic flow at the eight intersections. Traffic management at the UNI intersection resulted in the reduction in PM_{10} by about 23%, while for the TAB intersection the reduction is about 45%, which may be due to the nature of the intersection. Furthermore, the traffic management lowers the PM_{10} emission to accepted national limits (to lower than 120 μg/m^3). However, the particulate matter and PM_{10} are profoundly affected by weather conditions like humidity, wind speed and temperature (Mihăiță *et al.*, 2019). Although, the reduction in traffic emissions (both NO_2 and PM_{10}) was either neglected to be recorded or was relatively low at the intersections located in commercial centres like the city centre in Irbid city (BAR), as shown in Fig. 5.

4. CONCLUSIONS

Air quality in urban centres is highly dependent on

both traffic and weather conditions. Modelling air emissions will undoubtedly help improve the livelihood and health of people, especially at traffic hot spots. However, manipulating weather conditions is not an easy task. Therefore, traffic management is a necessary tool and approach to enhance people transportation and improve air quality in urban centres. Furthermore, in modelling environmental emissions and pollutants, it is an efficient and inexpensive tool that helps decision-makers, planning engineers and developers. Therefore, implementing a hybrid methodology will promote the modelling process and improve the quality of output used for predicting air pollution levels. This study has benefited from the capacity of VISSIM to analyse and suggest possible actions to improve the traffic flow and congestion at intersections. Likewise, the new (improved) traffic characteristics in this study were employed to anticipate the improvement of air quality using a previously developed ANFIS model. Indeed, ANFIS is a proven modelling tool that integrates the fuzzy logic and neural network. Implementation of these two stages in the modelling approach led to improving forecasting accuracy and minimising the cost of modelling and monitoring. Furthermore, it would assist city planners and decision-makers to properly understand the relationship between traffic and pollution in urban centres. As such, there is a need to undertake more in-depth analysis to enhance the integration of the model to improve the quality of prediction in this area.

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SUPPLEMENTARY MATERIALS

Table 1S. List of abbreviations.

Abbreviation	Meaning	Unit
VISSIM	Verkehr In tädten - SIMulationsmodell. It is a German word.	–
QLEN	Queue Length.	Meter (m)
V/C	Volume/Capacity.	%
Volume (V)	Actual Number of passing vehicles in a unit of time	Vehicle/hour
Capacity (C)	The maximum number of vehicles that can pass in a unit of time.	Vehicle/hour
Delay	The time difference between actual travel time and free- flow travel time.	Second/vehicle
ANFIS	Adaptive Neuro -Fuzzy Inference System	–