



Dynamic Linear Model for Urban Essential Traffic Congestion and Emissions

Alain Kibangou, Thembanani Moyo, Walter Musakwa

► To cite this version:

Alain Kibangou, Thembanani Moyo, Walter Musakwa. Dynamic Linear Model for Urban Essential Traffic Congestion and Emissions. CCA 2021 - Control Conference Africa, Dec 2021, Magaliesburg, South Africa. pp.1-6, 10.1016/j.ifacol.2021.12.026 . hal-03342467

HAL Id: hal-03342467

<https://hal.science/hal-03342467v1>

Submitted on 13 Sep 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Dynamic Linear Model for Urban Essential Traffic Congestion and Emissions

A.Y. Kibangou * T. Moyo ** W. Musakwa ***

* Univ. Grenoble Alpes, CNRS, Inria, Grenoble INP, GIPSA-Lab, Grenoble, France (e-mail: alain.kibangou@univ-grenoble-alpes.fr)

** Dept. of Urban and Regional Planning, University of Johannesburg, Doornfontein, 0184 Johannesburg, South Africa (e-mail: thembanijoel@gmail.com)

*** Future earth and Ecosystem Services Research Group, University of Johannesburg, Doornfontein, 0184 Johannesburg, South Africa, (e-mail: wmusakwa@uj.ac.za)

Abstract: Congestion is a phenomenon that impacts most cities in the world. Due to car emissions, it is a significant source of pollution. Even though mobility restrictions can reduce congestion and emissions, essential activities still need cars. With lockdown measures during the global pandemic of Covid-19, measuring essential traffic data has been made possible. This paper concerns analysis and modelling of such essential traffic. It appears that congestion dynamics of essential traffic exhibits dynamics than can be represented with a linear model. This paper introduces such a model and provide a method to jointly estimate the parameters and the model input. The model is validated with data collected in Johannesburg, South Africa.

Keywords: Essential traffic, Linear dynamic model, Parameter estimation, input design.

1. INTRODUCTION

Excessive reliance on the motor vehicle as a mode of transportation is the cause of urban dysfunction such as pollution, congestion, and space consumption. Congestion can be defined as a physical condition in traffic streams involving reduced speeds, restrained movements, extended delays and paralysis of the traffic network. Pollution due to road transportation mainly concerns two types of emissions:

- Greenhouse gas emissions which can trap additional heat from the sun in the earth's atmosphere, causing the 'greenhouse effect' and climate change. CO₂ is the main greenhouse gas produced by motor vehicles. The vehicle's level of CO₂ emissions is linked to the amount and the type of fuel consumed.
- Air pollutant such as carbon monoxide (CO), nitrogen oxides (NO_x), hydrocarbons (HC), particulate matter, volatile organic compounds and benzene are emitted into the environment by motor vehicles. Air pollutants can contribute to urban air quality problems, such as photochemical smog and adversely affect human health through respiratory illness, cardiovascular disease and cancer.

It is now well known that congestion and pollution levels are strongly related, Galatioto et al. (2014). If left uncontrolled, the use of the automobile would inexorably move the urban region away from sustainable development. There is therefore a need for collective efforts for the development of tools for monitoring and controlling congestion and pollution at a city level. Some cities, Grenoble (France) for instance, have implemented dif-

ferentiated traffic according to the age of the vehicle in case of high level of pollution. Due to Covid-19, mobility restrictions have led to a drastic decrease in congestion and car emissions. However, essential activities still need cars and contribute to pollution. Measuring congestion during lockdown periods provide a direct measurement of essential mobility. Understanding the dynamics of such essential mobility is crucial to define targets on mobility management.

Evaluating congestion as the travel time or delay incurred in excess of that in free flow conditions provide a strong basis for defining indicators that are easy to comprehend by the large public. Some relevant congestion indicators include the Speed Reduction Index (SRI), the ratio of the relative speed change between congested and free-flow conditions and the Relative Congestion Index (RCI): ratio of delay time and free-flow travel time; He et al. (2016); Rao and Rao (2012); Wan et al. (2018).

Previous studies reveal different strategies of assessing congestion and pollution trends. For instance, Chiabaut and Faitout (2021) utilised k-means algorithm and Gaussian mixture to visualise congestion maps in Lyon, France. Initially using k clusters, historical data-sets are categorised before merging with real-time data-sets to visualise the evolution of traffic patterns. Similar to other studies they proposed the use of the average speed of the observations to reduce the bias of recorded travel speed. There is also a growing body of research on utilising floating car data to assess road transportation, Jiang et al. (2011), Zhou et al. (2013). Examples include studies by Dasgupta et al. (2021) who assessed the congestion and pollution problem by using Google traffic data to model congestion and

pollution trends in Dar es Salaam (Tanzania). A regression model was used that incorporates a dynamic model of wind impact on the greenhouse gas. All these works have been carried out for general traffic patterns except Moyo et al. (2020) where a comparison between lockdown days and usual days is carried out in terms of emissions.

Using congestion measure at a city level, the aim of this paper is to study essential traffic, i.e. congestion patterns during mobility restrictions. The paper seeks to show that in an urban environment a linear dynamic model can well represent both congestion and emission dynamics. It is the first time essential congestion and emission are modeled. Moreover, modelling congestion as a mixture of step-responses of linear dynamic systems constitutes an original contribution.

The paper is organized as follows. In section 2, we formulate the problem under study which is solved in sections 3 and 4. The derived model is validated with real data in section 5. Then conclusions are drawn in section 6.

2. PROBLEM FORMULATION

The relative congestion index at time k , $c(k)$ is defined as the ratio of extra travel time $\Delta T(t)$ with respect to the free flow travel time T_f ; He et al. (2016); Wan et al. (2018):

$$c(k) = \frac{\Delta T(k)}{T_f} = \frac{T(k) - T_f}{T_f}. \quad (1)$$

If a model of the travel time $T(k)$ is available then one can deduce the one for $c(k)$. Travel time is usually modeled through time series analysis in order to understand the underlying mechanism that generates the observed data, which is used if for forecasting purpose. The main assumption of a time-series is that an observation at a given time depends only on its previous values and on a random noise. Curve fitting with radial basis functions for instance can also be used to get a static model of travel time and consequently for $c(k)$.

Actually, $c(k)$ can be viewed as the output of a dynamic system excited by an unknown input representing behaviour of drivers, transportation demand and other factors. The model of such dynamic system is unknown. For an usual traffic day, complicated dynamics are involved and lead to complex nonlinear dynamic systems. However, with the COVID-19 pandemic, almost all countries regularly implement mobility restrictions. For some specific time windows, only mobility related to essential activities is allowed. The related traffic is called hereafter as *essential traffic*. The purpose of this paper is to study precisely the dynamics of essential traffic by modelling both the unknown input and the dynamic system itself.

From the observed data (see Fig. 1 that depicts the dynamics of the congestion index during working days for usual days and for days under lockdown), essential traffic dynamics seem to be less aggressive and could be modelled with a linear system. Furthermore, the impact of congestion in terms of emissions $\epsilon_t(k)$ of air pollutant of type t (see section 4) has been modelled with some nonlinear static functions. As a consequence, emission $\epsilon_t(k)$ can be viewed as the output of a Wiener system (a cascade of linear dynamic system with a static nonlinear function).

We aim at showing that in an urban environment a linear approximation is valid and then yields a linear dynamic system for representing $\epsilon_t(k)$. In contrast to time-series modelling which involves noise as external signal, here we assume a deterministic input signal with possibly a physical meaning.

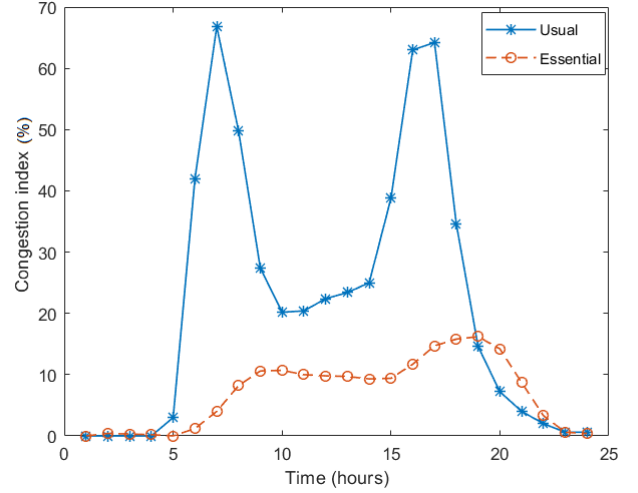


Fig. 1. Average congestion index during working days: usual traffic (2019) vs essential traffic as recorded during lockdown in Johannesburg (2020).

3. MODELLING DYNAMICS OF ESSENTIAL TRAFFIC

In this section, we derive a dynamic linear model and its input $u(\cdot)$, in order to reconstruct the congestion index $c(k)$ during an essential traffic day.

3.1 Model structure

From Fig. 1 one can note a significant reduction of the congestion. In addition, while usual traffic exhibits two huge peaks with same levels at morning and evening rush hours, only the evening peak can be noted for the essential traffic. Traffic during usual days can be segmented into three periods: (i) going to work (morning peak), (ii) working time (noon plateau), (iii) going back home (evening peak). For essential traffic the two first periods are merged. One can think to model the process as the response of a possibly linear system to a step-wise constant signal. We propose the following model for the input

$$x(k) = \begin{cases} 0, & 1 \leq k < k_0 \\ K_0, & k_0 \leq k < k_1 \\ K_1, & k_1 \leq k \leq k_2 \\ 0, & k_2 \leq k \leq 24 \end{cases}$$

with unknown magnitudes K_0 and K_1 and step times k_i , $i = 0, 1, 2$ to be defined from observed data. For the example in Fig. 1, one can set $k_0 = 6$, $k_1 = 15$, and $k_2 = 21$. The unknown input $x(k)$ can therefore be represented as the sum of three delayed steps as:

$$x(k) = u_0(k) + u_1(k) + u_2(k), \quad (2)$$

where $u_i = A_i u(k - k_i)$, $u(\cdot)$ standing for a unit step: $u(k) = 1$ if $k \geq 0$ and $u(k) = 0$ elsewhere. The magnitudes and the time delays A_i and k_i , $i = 0, 1, 2$, are to be estimated from data.

Having linear system's step-responses in mind, from Fig. 1, one can note overshoots in response to $u_0(\cdot)$ and $u_1(\cdot)$. This leads to adoption of second-order transfer functions to represent dynamics of congestion. Precisely the following model structure is proposed, where

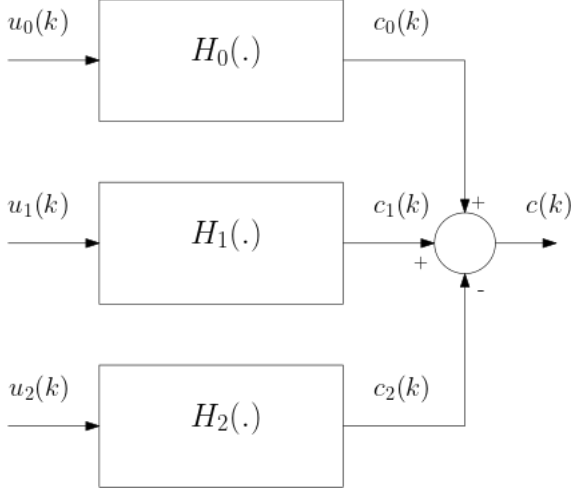


Fig. 2. Model structure for congestion index.

$$H_i(z) = \frac{1}{1 + a_i z^{-1} + b_i z^{-2}}.$$

Using difference equations, the proposed model is as follows:

$$c(k) = \sum_{i=0}^2 c_i(k) + \nu(k), \text{ with} \quad (3)$$

$$c_i(k) = -a_i c_i(k-1) - b_i c_i(k-2) + A_i u(k - k_i).$$

where $\nu(k)$ stands for the modelling error.

3.2 Physical interpretation of the input

The first and the second inputs define the instant where morning and afternoon congestion waves start. Their amplitude can be related to the level of congestion in steady state, if there was only one wave. $u_0(\cdot)$ represents essential congestion generator while $u_1(\cdot)$ can be viewed as essential congestion damper. The last signal $u_2(\cdot)$ allows dissipating the remanent effects of the congestion caused by the first two signals. The underlying assumption is that a congestion wave cannot subside on its own. Hence the need to add this third signal that brings the system back to rest.

3.3 Parameter estimation

Defining $\theta_i = (a_i, b_i, A_i)^T$, $i = 0, 1, 2$, thanks to the delayed step nature of the inputs and setting $c(k) = 0$ for $k < k_0$, one can note that:

- for $k = k_0, k_0 + 1, \dots, k_1 - 1$,
 $c(k) = \psi_0^T(k) \theta_0 + \nu(k),$ (4)
with $\psi_0^T(k) = (-c(k-1), -c(k-2), 1).$

- for $k = k_1, k_1 + 1, \dots, k_2 - 1$
 $\tilde{c}(k) = c(k) - c_0(k) = \psi_1^T(k) \theta_1 + \nu(k),$ (5)
with $\phi_1^T = (-\tilde{c}(k-1), -\tilde{c}(k-2), 1)$

- for $k = k_2, k_2 + 1, \dots, 24$
 $\tilde{\tilde{c}}(k) = \tilde{c}(k) - c_1(k) = \phi_2^T(k) \theta_2 + \nu(k),$ (6)
with $\phi_2^T = (-\tilde{c}(k-1), -\tilde{c}(k-2), 1).$

Denoting

$$\Psi_i = (\psi_i(k_i) \ \psi_i(k_i + 1) \ \dots \ \psi_i(k_{i+1})) , i = 0, 1, 2$$

and

$$\nu_i = (\nu(k_i) \ \nu(k_i + 1) \ \dots \ \nu(k_{i+1})) , i = 0, 1, 2$$

where $k_3 = 24$, in matrix form we get:

$$\gamma_0 = \begin{pmatrix} c(k_0) \\ c(k_0 + 1) \\ \vdots \\ c(k_1 - 1) \end{pmatrix} = \Psi_0 \theta_0 + \nu_0 \quad (7)$$

$$\gamma_1 = \begin{pmatrix} \tilde{c}(k_1) \\ \tilde{c}(k_1 + 1) \\ \vdots \\ \tilde{c}(k_2 - 1) \end{pmatrix} = \Psi_1 \theta_1 + \nu_1 \quad (8)$$

$$\gamma_2 = \begin{pmatrix} \tilde{\tilde{c}}(k_2) \\ \tilde{\tilde{c}}(k_2 + 1) \\ \vdots \\ \tilde{\tilde{c}}(k_3) \end{pmatrix} = \Psi_2 \theta_2 + \nu_2 \quad (9)$$

The parameters are then estimated by solving sequentially the optimization problems:

$$\hat{\theta}_i = \underset{\theta_i}{\operatorname{argmin}} ||\gamma_i - \Psi_i \theta_i||^2, \quad i = 0, 1, 2.$$

The solutions are given by

$$\hat{\theta}_i = \Psi_i^\dagger \gamma_i, \quad i = 0, 1, 2. \quad (10)$$

4. LINEAR MODEL FOR CONGESTION TO EMISSIONS.

In this section we aim at deriving a linear approximation to a static function that maps congestion $c(k)$ to emission $\epsilon_t(k)$. In what follows, we drop the time index k since we are dealing with a static map.

From definition (1) of the congestion index, with few algebraic operations we can link the average speed V with the free flow speed V_f as

$$V(c, V_f) = \frac{V_f}{1 + c} \quad (11)$$

For a given free flow speed V_f , the average speed is then a strictly decreasing function of the congestion index.

Several factors influence the fuel consumption and emissions of vehicles, including vehicle speed, loaded weight, model year, road grade, road type, and congestion level. Emissions due to road transportation can be derived using either macroscopic, microscopic, or mesoscopic models (see Othman et al. (2019) for a review of such models). Recent years have seen several attempts to model emissions or fuel

consumption using macroscopic variables as the average speed; Boriboonsomsin et al. (2012); Song et al. (2013). We aim at developing a congestion to emissions index as a function of the congestion index and analyze its properties.

In Boriboonsomsin et al. (2012), emissions of type t have been modeled as:

$$\epsilon_t(V) = \frac{\alpha_t}{V} + \sum_{l=0}^2 \beta_{k,t} V^l. \quad (12)$$

Parameters a_t and $\beta_{k,t}$ depend on the type of the vehicle and the type of pollutant (HC, NO_x, CO, CO₂).

Table 1. Regression coefficients for Light duty vehicles Song et al. (2013)

t	α_t	$\beta_{0,t}$	$\beta_{1,t}$	$\beta_{2,t}$
HC	10.8	-7.11×10^{-3}	3.76×10^{-4}	3.63×10^{-5}
NO _x	2	-4.49×10^{-2}	-3.36×10^{-4}	3.49×10^{-5}
CO	80.8	1.16	5.03×10^{-3}	5.35×10^{-4}
CO ₂	4780	111	-1.24	2.37×10^{-2}

It can be shown that for $V > 0$, $\epsilon_t(V)$ is a convex function with a single minimum at V_m , the unique real root of the polynomial $P(V_m) = 2\beta_{2,t}V_m^3 + \beta_{1,t}V_m^2 - \alpha_t$, which is the numerator of the first derivative of $\epsilon_t(V)$. Table 2 gives the values of V_m for different t .

Table 2. Values of V_m (km/h) with minimum emissions level for different air pollutants.

HC	NO _x	CO	CO ₂
51.31	32.29	40.76	57.09

Figure 3 depicts $\epsilon_t(V)$ for CO₂. One can note that after

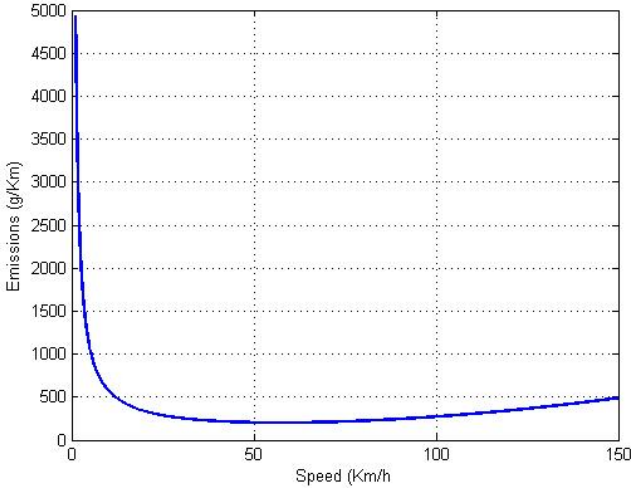


Fig. 3. CO₂ emission with respect to average speed

V_m the emissions increase slowly with the speed. In what follows we show that, for an operational average speed $V \leq V_{max}$, we can approximate $\epsilon_t(V)$ by a decreasing function:

$$\tilde{\epsilon}_t(V) = \frac{a_t}{V} + b_t. \quad (13)$$

Values of a_t and b_t , can be obtained by minimizing the cost function

$$J(a_t, b_t) = \frac{1}{N+1} \sum_{n=0}^N \left(\epsilon_t(V_n) - \frac{a_t}{V_n} - b_t \right)^2,$$

with $0 < V_n \leq V_N = V_{max}$.

Example: For $V_0 = 1$ Km/h, $V_n = V_n - 1 + 0.01$, $n = 1 : N - 1$ and $V_N = V_{max} = 70$ Km/h, we have found the values $a = 4.632 \times 10^3$ and $b = 48.428$ for CO₂ emissions. Fig. 4 shows how good is the approximation.

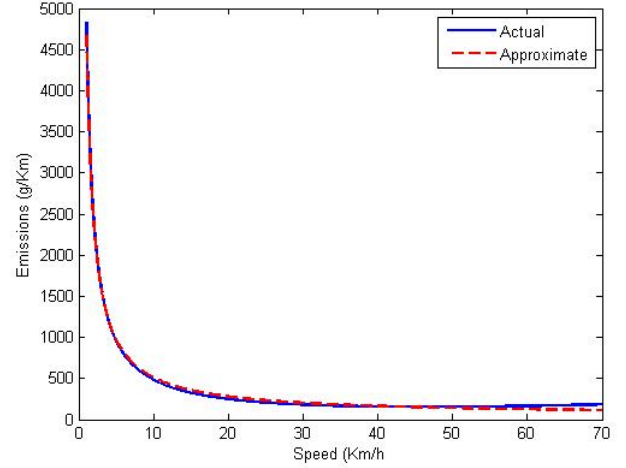


Fig. 4. Approximation of CO₂ emission

Proposition 1. For a free flow speed V_f and a congestion index c , emissions for essential traffic in an urban environment can be well approximated as

$$\epsilon_t(c, V_f) = \epsilon_t(0, V_f) + \frac{a_t}{V_f} c, \quad (14)$$

with $\epsilon_t(0, V_f)$ the emissions at congestion free given by $\epsilon_t(0, V_f) = \frac{a_t}{V_f} + b_t$.

Proof. Equation (14) is obtained by substituting in (13) the speed by the expression (11).

The model for emission of type t can then be reproduced by the model depicted in Fig. 5.

5. MODEL VALIDATION

We consider congestion trends for the city of Johannesburg for model validation purpose. As the economic hub of South Africa, numerous commuters travel into and out of the city on a daily basis. This has led to a situation of commuters experiencing high levels of congestion during the peak hours. In early 2020, there was a global outbreak of the Corona virus (COVID-19). As a response to this pandemic, Saladié et al. (2020) and WHO (2020) outlined that many nations introduced movement restrictions to reduce the spread of the virus. In South Africa, the first mobility restriction was announced on the 23rd of March 2020 to take effect on the 26th of March 2020; Gilbert et al. (2020); Moyo et al. (2020). During the initial 21 days lockdown, the only movement for providing essential services was permitted. As part of the shutdown, movement between provinces, metros and district areas

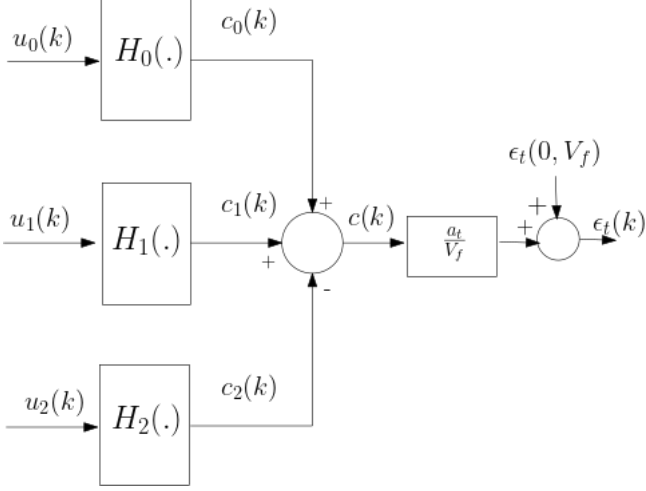


Fig. 5. Dynamic linear model for emission of type t .

was banned. To facilitate movement by essential workers public transport for essential trips was restricted, in the morning between 05:00 to 09:00 and evening between 16:00 to 20:00. Nyabadza et al. (2020).

Google (2020) reveals mobility trends during the pandemic in developing cities such as Johannesburg have decreased, which has led to a drastic reduction of congestion on major roads. Figure 6 outlines notable mobility trend changes from baseline due to lockdown regulations from 20/04/2021 to 26/04/2021. Recreation and retail trips have had -3 percent change compared to the baseline; Trips made using public transportation have had -19 percent change compared to the baseline; and lastly Workplace trips have had a decline of -12 percent change compared to the baseline.

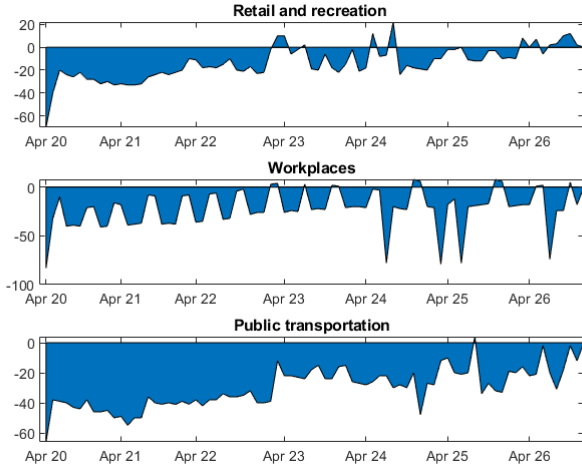


Fig. 6. Percentage of mobility change from baseline

TomTom Congestion Index was collected from April 14th to 27th. Given the city of Johannesburg road network which consists in urban arterial and highways we limit the free-flow speed to 50 Km/h.

In Figure 7, we can note that a good reconstruction of congestion index is obtained with the proposed linear model. The parameters were set to $k_0 = 7h$, $k_1 = 15h$,

$k_2 = 21h$. However, while k_0 , start time of the first step can be easily detected and k_1 can be inferred from commuters behaviour, detecting k_2 is more challenging.

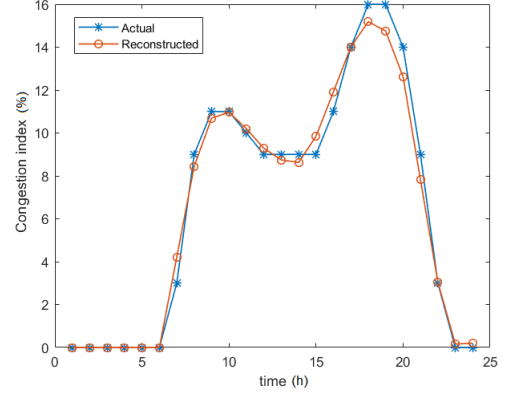


Fig. 7. Model validation - data for April 16th, 2020.

In table 3, we evaluate the Root mean square reconstruction error for different choices of (k_0, k_1, k_2) . For this purpose, we set $k_0 = 7h$, $k_1 = 14h, 15h, 16h$, and $k_2 = 20h, 21h, 22h$. The results are given in Table 3. One can note that the best hour for the second step input is $k_1 = 16h$ for all the evaluated dates. For k_3 , 21h is the most likely hour.

Table 3. Root Mean Square Reconstruction Error and best selection of k_1 and k_2 for various working days

Date	Best k_1	Best k_2	RMSE
April 14	16h	20h	0.531
April 15	16h	22h	0.485
April 16	16h	21h	0.367
April 17	16h	20h	0.347
April 20	16h	21h	0.265
April 21	16h	21h	0.367
April 22	16h	22h	0.403
April 23	16h	21h	0.241
April 24	16h	21h	0.242
April 27	16h	20h	0.291

6. CONCLUSION

The paper has presented a dynamic linear model for urban essential traffic congestion and emission. The validated model consists in three IIR second-order filters excited by delayed step inputs. Magnitude and time delays can be related to the transportation demand and to working time schedules. The parameters of the model are identified using a least squares method. For the average free flow speed in an urban context, the mapping between congestion and emissions can be well approximated with a linear function giving rise to a linear dynamic model for emissions reconstruction. As future works, using this model, extraction and forecasting of essential traffic from usual one will be investigated. In addition, it could be interesting to explore the link between the magnitude of the unknown input signal with the transportation demand, which can constitute a control variable.

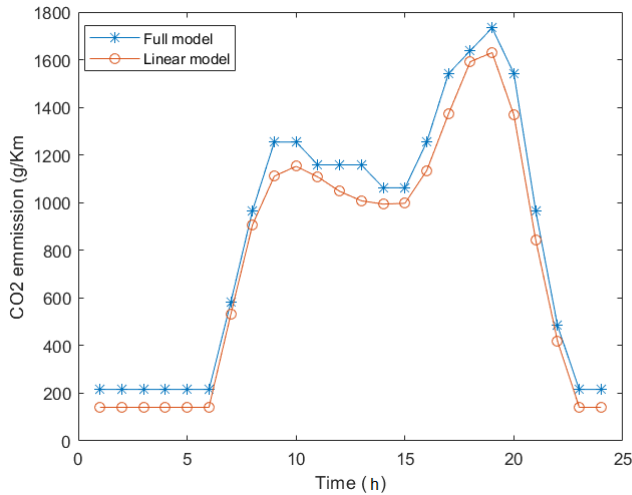


Fig. 8. Comparison of CO₂ emissions during a day.

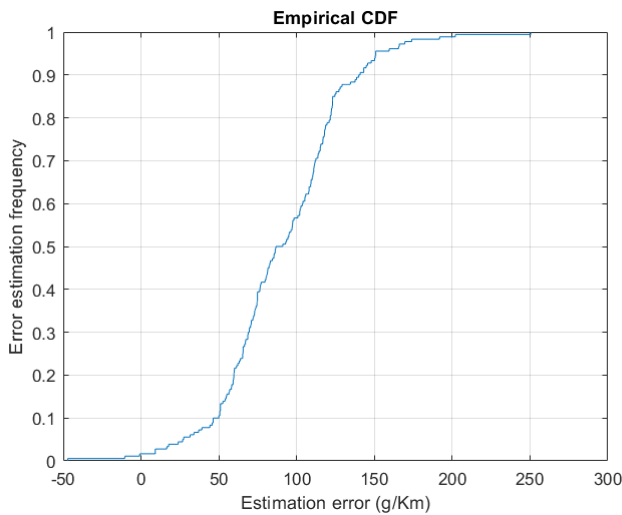


Fig. 9. Empirical cumulative distribution function of the estimation error.

ACKNOWLEDGEMENTS

This work is partly supported by the National Research Foundation South Africa, Grant Number 129925, South Africa/France (Protea) Joint Research Programme-PercepTrans project.

REFERENCES

Boriboonsomsin, K., Barth, M., Zhu, W., and Vu, A. (2012). Eco-routing navigation system based on multi-source historical and real-time traffic information. *IEEE Trans. on Intelligent transportation Systems*, 13(4), 1694–1704.

Chiabaut, N. and Faitout, R. (2021). Traffic congestion and travel time prediction based on historical congestion maps and identification of consensual days. *Transportation Research Part C: Emerging Technologies*, 124.

Dasgupta, S., Lall, S., and Wheeler, D. (2021). Spatiotemporal analysis of traffic congestion, air pollution, and exposure vulnerability in tanzania. *Science of The Total Environment*, 147114.

Galatioto, F., Bell, M.C., and Hill, G. (2014). Understanding the characteristics of the microenvironments in urban street canyons through analysis of pollution measured using a novel pervasive sensor array. *Environmental monitoring and assessment*, 186(11), 7443–7460.

Gilbert, M., Pullano, G., Pinotti, F., Valdano, E., Poletto, C., Boëlle, P.Y., d’Ortenzio, E., Yazdanpanah, Y., Eholie, S.P., Altmann, M., et al. (2020). Preparedness and vulnerability of african countries against importations of covid-19: a modelling study. *The Lancet*, 395(10227), 871–877.

Google (2020). Covid-19 community mobility report. URL <https://www.google.com/covid19/mobility/>.

He, F., Yan, X., Liu, Y., and Ma, L. (2016). A traffic congestion assessment method for urban road networks based on speed performance index. *Procedia Eng.*, 137, 425–433.

Jiang, G.y., Chang, A.d., Li, Q., and YI, F. (2011). Estimation models for average speed of traffic flow based on gps data of taxi. *Journal of southwest jiaotong university*, 46(4), 638–644.

Moyo, T., Kibangou, A., and Musakwa, W. (2020). Exploring the Potential of Traffic Index Data to Analyze Essential Traffic Impact in Developing Cities. In *ISPRS 2020 - XXIV ISPRS Congress International Society for Photogrammetry and Remote Sensing*, volume XLIII-B4-2020, 137–141. Nice (online), France.

Nyabadza, F., Chirove, F., Chukwu, W.C., and Visaya, M.V. (2020). Modelling the potential impact of social distancing on the covid-19 epidemic in south africa. *medRxiv*.

Othman, B., De Nunzio, G., Domenico, D.D., and Canudas de Wit, C. (2019). Ecological traffic management: A review of the modeling and control strategies for improving environmental sustainability of road transportation. *Annual Reviews in Control*, 48, 292–311. doi:10.1016/j.arcontrol.2019.09.003.

Rao, A.M. and Rao, K.R. (2012). Measuring urban traffic congestion-a review. *International Journal for Traffic & Transport Engineering*, 2(4).

Saladié, Ò., Bustamante, E., and Gutiérrez, A. (2020). Covid-19 lockdown and reduction of traffic accidents in tarragona province, spain. *Transportation research interdisciplinary perspectives*, 8, 100218.

Song, Y.Y., Yao, E.J., Zuo, T., and Lang, Z.F. (2013). Emissions and fuel consumption modeling for evaluating environmental effectiveness of ITS strategies. *Discrete Dynamics in Nature and Society*, 2013.

Wan, C., Yang, Z., Zhang, D., Yan, X., and Fan, S. (2018). Resilience in transportation systems: A systematic review and future directions. *Transp. Rev.*, 38, 479–498.

WHO (2020). Coronavirus disease 2019 (covid-19): World health organization situation report, 72.

Zhou, X., Wang, W., and Yu, L. (2013). Traffic flow analysis and prediction based on gps data of floating cars. In *Proceedings of the 2012 International Conference on Information Technology and Software Engineering*, 497–508. Springer.