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Modelling Energy Consumption of Freight Road with MLR

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Abstract

Actually multiple linear regression is widely used in data processing in industry, organizational behavior, marketing, management and social sciences...

This paper presents a way to analyze and situate the impact of a set of factors on diesel fuel consumption, which allows company managers to make the right choice in terms of vehicle purchase at the tactical level and driver behavior at the operational level, it follows a methodological approach based on statistical methods, these methods make it possible to extract regression models with several predictors, the impact of each predictor is analyzed and processed using the identified statistical indicators.

This article presents a correlation study of factors related to vehicle characteristics and driver behavior as a result of multiple regression models with 118 traffic data records for 28 vehicles, to analyze the causal relationship between factors and energy consumption in a Moroccan industrial enterprise.

The analysis presented shows that many of the factors have an impact on the energy consumption of road freight transport. The R, R-squared and student test values indicate a strong relationship between fuel consumption and different factors studied.

Table of abbreviations:

SCM	Supply Chain Management
RFT	Road Freight Transport
CO_2	Carbon Dioxide
FP	fiscal power
GVWR	gross vehicle weight rating
EW	Empty weight
ρ	Coefficient of Pearson
γ	Acceleration (m²/s)
V_n	Vehicle n
V_{max}	Maximum speed
Y_i	Energy consumption (L / 100 km) according to the model i

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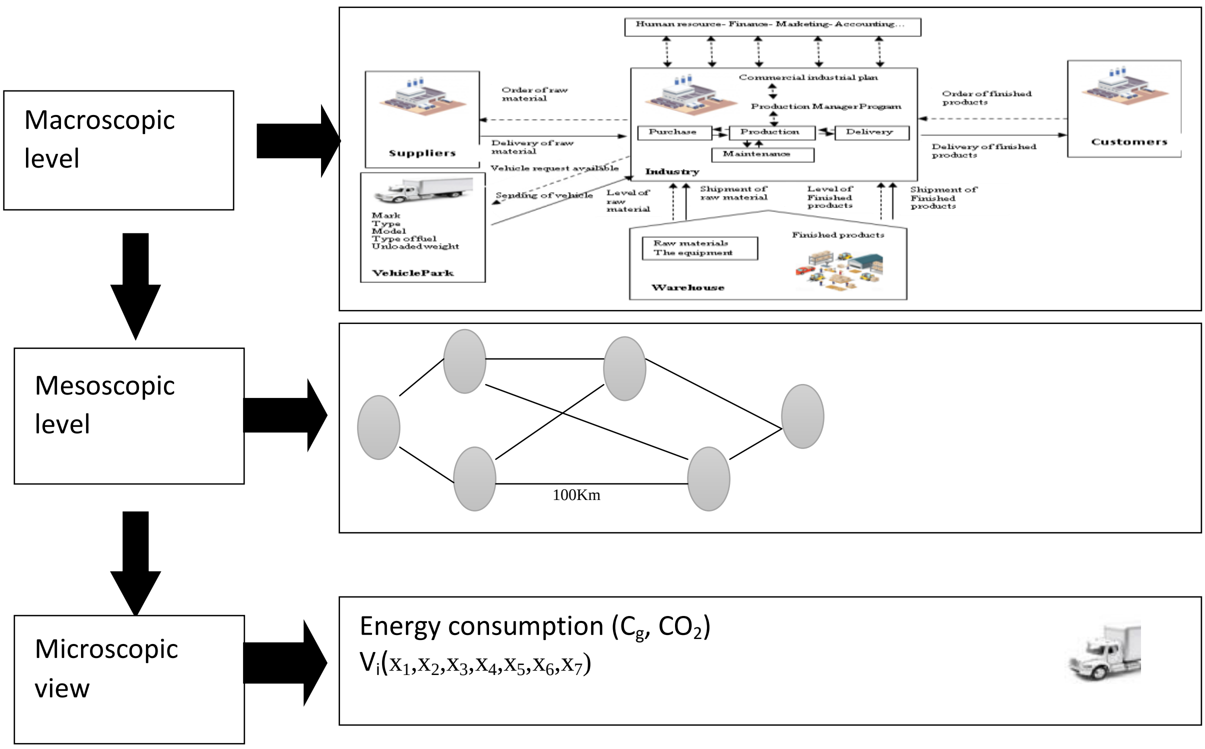
I. Introduction

In the last century, there has been a dramatic increase in economic activity around the world. One of the side effects of the increase in economic activities is the increase in the use of transport modes and consequently the increase in CO_2 emissions.

The uncontrolled and poorly planned growth of freight transport has led to several problems such as road congestion, environmental pollution, the deterioration of public health[1], So Carbon dioxide (CO_2) emissions are related not only to the distance traveled by the vehicle, but also to the characteristics of vehicles, driver behavior on the road, strategic choices of the company, infrastructure, etc ... According to the literature, the fuel consumption and the CO_2 emissions are strictly interconnected, But this relationship is not applicable to other air pollutants, such as particulate matter, NOx and CO[2][3].

This paper classifies the factors of fuel consumption on three levels (macroscopic, mesoscopic and microscopic) each model is modeled by a multiple regression function to measure the impact of each factor and reformulate the general prediction function.



Model 1 : $Y_1=a_{11}x_1+a_{12}$

Model 2 : $Y_2=a_{21}x_1+a_{22}x_2+a_{23}x_3+a_{24}x_4+a_{25}x_5+a_{26}$

Model 3 : $y_3= a_{31}x_1+a_{32}x_6+a_{33}x_7+a_{34}$

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Vehicle energy consumption $Y_i=\sum a_{ij}\, x_k$ is a multi-variable function influenced by internal factors related to the characteristics of vehicles (GVWR, **EW**, FP, Age ...) and external factors related to the driver, speed, infrastructure, climate…

The prediction of CO_2 emissions has become an important research as it would provide clues and raise awareness of environmental stability.

Emissions of gaseous elements such as CO_2 are becoming a global concern as greenhouse gases have the greatest impact on environmental problems.

Nevertheless, choosing the right methods to predict CO_2 emissions depends on a wide range of factors that involved both qualitative and quantitative variables.

II. The data collection

A fleet of 74 vehicles of different categories was studied for one year with 56 different drivers. The company in question is an innovative olive oil industrial company in the Moroccan agri-food sector, For more than 50 years, data on the consumption of diesel fuel has been taken on a sample of 28 vehicles of different brands with a GVWR of 3, 5 tons up to 40 tons, the tracking operation by Global Positioning System (GPS) and Tachograph disk was essential in the speed and acceleration recording stage for this tracking two trailers of 19 tons and 40 tons is enough.

The purpose of this section is to assess the impact of a combination of factors on energy consumption with dynamic traffic conditions, on the basis of the results obtained, we can deduce the nature of the instantaneous emissions.

These data are presented in the following annexes (1 and 2) that represent the fuel consumption as a function of speed, acceleration; GVWR, EW, FP and Vehicle Age, which describe the relationship between CO_2 emissions and the proposed variables.

III. Methodology

III.1. mesoscopic modeling

In order to estimate emissions, three different approaches have been defined in recent years: macroscopic, mesoscopic and microscopic.

the macroscopic view is an overall panoramic view of the entire logistics chain of the company, based on knowledge of the company's fleet vehicle, delivery quantities, subcontracting of means of transport, alliance strategy with other companies, the use of global network parameters such as the values of the slope of the road, the nature of the journey ...,[4][5][6].

The accuracy of this view is low, because no information is taken into account concerning the characteristics and the specific power of each vehicle, the speed, the loading rate, the acceleration time, the deceleration time ..., for this reason the minimization of energy consumption does not simply depend on the macroscopic approach there are other factors related to vehicles, driver behavior and also to the road and climate that are much more relevant to take into account.

The mesoscopic view is a reduced view compared to the macroscopic view, focused on a targeted process, builds synthetic training cycles and is an interesting alternative to microscopic models if detailed data on speed and acceleration are not available [7].

The microscopic view can significantly improve the emission estimate, but it is generally applied to a subset of network links (100km) because it requires huge input data depending on [8].

The linear relationship between two variables is usually explained by a linear regression model [9]. Linear regression was the first type of regression analysis to be rigorously studied and used extensively in many practical applications. So at

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the mesoscopic level we chose to evoke the model 1 which reflects the impact of the vehicle class on energy consumption and model 2 which explains the impact of FP, AGE, GVWR and EW.

Finally in the microscopic view we generated the model 3 which is interested in studying the impact of speed and acceleration on fuel consumption, these two parameters reflect the impact of driver behavior on consumption without forgetting obviously the social aspect in the control of the traffic standards and the management of the risks of the road

III.1.1. Mesoscopic factors affecting energy consumption

The Pearson (ρ) factors of GVWR, FP, EW successively presented in Table 1 are ($\rho_{\mathbf{GVWR}}$= 0.963), (ρ_{FP} = 0.954) and ($\rho_{\mathbf{EW}}$ = 0.961), show the level of impact of each variable on consumption. The values of ρ> 0.7 are close to the correlation line, which indicates a strong linear relationship between the variables, whereas the vehicle age (ρ_{Age} = 0.121) has a low correlation coefficient which allows to neglect this variable in future considerations.

Table 1: correlation between variable

		Ratio (L/100Km)	GVWR (T)	Age	FP	EW(T)
Pearson correlation (ρ)	Ratio (L/100Km)	1,000	0,963	0,121	0,954	0,961
	GVWR (T)	0,963	1,000	0,085	0,965	0,899
	Age	0,121	0,085	1,000	0,032	0,212
	FP	0,954	0,965	0,032	1,000	0,900
	EW(T)	0,961	0,899	0,212	0,900	1,000

Bi-varied correlation analyzes and multiple regression analyzes have been applied throughout this section however, the bi-varied correlation analysis reflects how the two variables are correlated, but the presence of a strong correlation between two variables does not assert a causal relation, To check if there is a cause-and-effect relationship between the variables, we must take into account the effects of the independent variables, this is done by multiple regression analysis.

A multiple regression model is a linear model with multiple predictors or regressors [10], the purpose of multiple regression is to learn more about the relationship between several independent variables and a dependent variable. In general, multiple regression analysis allows the researchers to ask the following question: What is the best predictor of...?

Also the multiple regression analysis allows us to integrate the variation of several variables in the same analysis and to isolate the effects of single independent variables.

In this section we will analyze the quality of the obtained models (1 and 2) through the study of the R or R-squared indicator and the F Test which help us to compare the predicted values of the dependent variable with the values real.

the values of R and R-square are between 0 and 1 plus the value of R-square is important plus the model explains the phenomenon, in our case the R-square of model 1 is 0.927 and of model 2 is 0.988, which means that the explanatory variables of models 1 and 2 contribute 92.7% and 98.8% successively to the variable to explain, namely energy consumption.In general if the R-square value is greater than 0.3 we can confirm the results.

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the R-squared values for both models show good explanatory and predictive capabilities of the models according to Table 2, the variation of F tests whether the most recent contribution shows a significant improvement in the prediction capacity of the regression equation, for this we must see the value of the variation of F and its significance value, in both models we notice that the variation of F is very significant, which allows us to say that the regression equation is significant and the explanatory variables contribute very significantly to the ratio variable scores (L / 100km) of energy consumption.

Before moving on to standardized regression coefficients one has to analyze the model validity through the examination of residues more particularly the Durbin-Watson test (DW) and the graphs examination for that the last column of table 2 presents this test.

The test (DW) is used to evaluate the relationship between the residues and the errors, the Durbin Watson test value varies between 0 and 4 and it will confirm or invalidate the hypothesis of independence between the residues, to ensure that the residues are not correlated it is necessary that the value of test of Durbin Watson is close to 2 that is to say in absolute value between 1.50 and 2.50, in our case the Durbin Watson test indicates a value of 2.022 this is a limit value in the safety interval that confirm that the residuals are not correlated and that the regression model is valid.

Table 1: the contribution of the different predictors

Models	R	R-squared	R-squared adjusted	Standard estimation error	Edit statistics			Durbin - Watson
					R-squared variation	F Variation	Sig of F variation	
1	0,963[a]	0,927	0,924	2,41	0,927	340,519	0,000	
2	0,988[b]	0,976	0,972	1,46	0,049	16,288	0,000	2,022
a. predictors : (Constant), GVWR (T)								
b. predictors : (Constant), GVWR (T), Age, EW(T), FP								
c. Dependent variable: Ratio (L/100Km)								

Following the mesoscopic analysis of the consumption of vehicles, model 1 and 2 help to predict the consumption envisaged and at this level, the decision to purchase a new vehicle or subcontracting and route choices are essentially related to the technical characteristics of the vehicle which can increase or decrease the consumption according to the strategic decision taken.

After the validation of the models we will analyze the relationship between the explanatory variables and the variable to be explained through the standardized regression coefficient Beta, student test and significance test, Table 3 contains the Beta regression coefficients, student test and significance test, the standardized beta coefficient is interpreted in the same way as the Pearson regression coefficient, so if beta is less than the absolute value of 0.29 the effect is low if beta in absolute value is between 0.3 and 0.49 the effect is medium and if beta is greater than 0.5 in absolute value the effect is strong.Student's T test is used to test the significance of a regression coefficient, in Table 3 the coefficients show that the vehicle GVWR for model 1 has a large effect on consumption and for model 2 the GVWR and EWhave a significant effect with a p-value <0.01 however the Age and the FPdo not have a

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significant impact in summary the highest Beta coefficient that has a big impact on the energy consumption.
After taking into account the above aspects, the regression analysis was carried out to evolve the model 1 and the model 2 with its four parameters, the estimated coefficients and the associated statistics displayed in table 3.

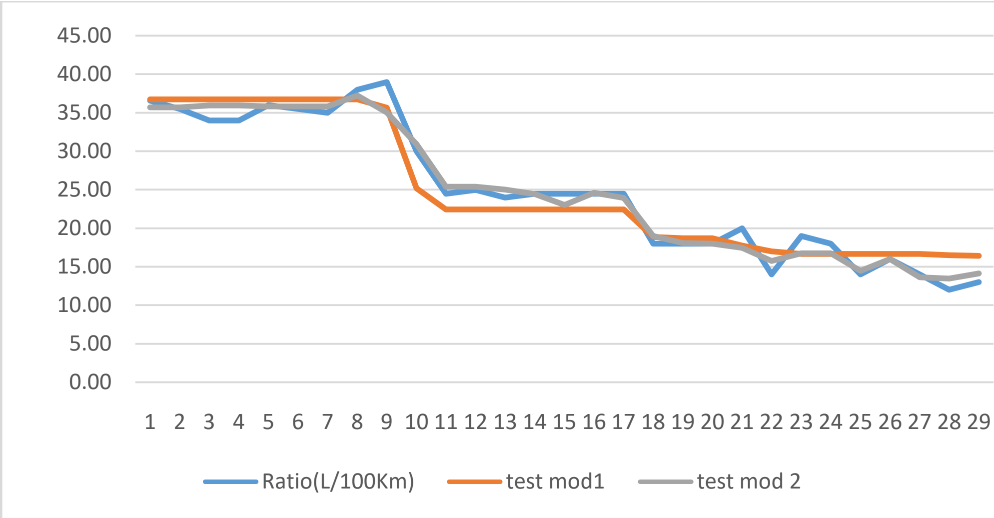

Figure 1: model deviations from the actual model

The prediction according to model 2 with a (R^2 = 0,9758)compared to model 1 (R^2=0,927)
is closer to reality according to Figure 2, so the consumption is not simply related to the vehicle weight but there are other vehicle characteristics that influence the consumption on the road.

The non-standardized coefficients allow us to reconstruct the equation of the regression line of model 1 and model 2, so in this case
the model 1: Y_1=0,55* GVWR+14,744
the Model 2: Y_2=0,232 * GVWR+0,119*FP+2,188*EW-0,032*Age+ 8,260

Table2: The functions of the multiple regression model 1 and 2

Models		Unstandardized coefficients B	Unstandardized coefficients Standard error	Standardized coefficients Bêta	t	Sig.
1	(Constant)	14,744	0,706		20,895	0,000
	GVWR (T)	0,550	0,030	0,963	18,453	0,000
2	(Constant)	8,260	1,531		5,394	0,000
	GVWR (T)	0,232	0,072	0,406	3,195	0,004
	Age	-0,032	0,052	-0,022	-0,625	0,538
	FP	0,119	0,134	0,118	0,891	0,382
	EW(T)	2,188	0,706	0,494	6,033	0,000

Microscopic factors affecting energy consumption

According to Wisetjindawat et al. [11]Microscopic modeling aims to collect data parameters such as flow, density, speed, travel time, long queues, stops, pollution, fuel consumption and shock waves.The characteristics of this modeling were based on the vehicle tracking model, the lane change models and the causes of disruption of individual drivers[12], [13].

The database used is recovered from a Moroccan industrial company with a fleet of vehicles, these data allow the study of the impact of the vehicle classGVWR, EW,FP and Age with the models 1 and 2, as well as the speed and acceleration with model 3 according to Table 4.

Fuel consumption and emissions are strictly related to speed and acceleration profiles that often depend on two categories of parameters: traffic conditions and driving behavior.

The first category includes the maximum speed limit and the theoretical acceleration rate, which vary according to the characteristics of the infrastructure, the actual speed, the acceleration rate and the number of vehicle stops due to congestion and the flow of the road network. The second category takes into account the different driving behaviors of the users, from a physical point of view, driving behavior is represented by speed-time and acceleration time charts.

Analyzing the entire fleet vehicle is not obvious because of time consumed and the variety of behaviors of drivers which can generate more error in the development of model 3, for this reason the registration of 118 catches of two categories of vehicles (V_1= 19 tons et V_2=40 tons) is sufficient to provide a multi-variable function (speed, acceleration) showing the level of impact of each factor on energy consumption and CO_2 emissions.

To achieve this plan, speed optimization has become a typical way to improve fuel efficiency, as it would reduce engine power or fuel consumption three times faster [14].

The linear relationship between a response variable and several predictors is explained by several linear regressions, However, in many practical applications, multiple predictors may be associated with a response variable [15].

Multiple regression analysis was considered as a way to describe the relationship between energy consumption and a plurality of predictors (GVWR, speed and acceleration) this relationship can help predict the response variable (energy consumption) according to the Table 5.

Table3: Model 3 summary 3

					Edit statistics			
Model	R	R-squared	R-squared adjusted	Standard error of estimate	R-squared variation	F Variation	Sig. Of F Variation	Durbin-Watson
3	0,812[a]	0,659	0,650	174243%	0,659	73,343	0,000	0,950
a. predictors : (Constant), □ (m/s²), Vmax (Km/h), GVWR (T)								
b. Dependent variable: % Consumption (L/100km) real								

The general formula obtained in the microscopic level is:

$$\mathbf{Y}_3=30{,}545+0{,}278*GVWR-0{,}057*Vmax+0{,}168*\gamma$$

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Table 4: the multivariable function of model 3

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Standard error	Bêta		
3	(Constant)	30,540	1,055		28,938	0,000
	GVWR (T)	0,278	0,023	0,981	12,223	0,000
	Vmax (Km/h)	-0,057	0,016	-0,276	-3,510	0,001
	$\gamma\ \sigma/\mu(^2)$	6,168	21,610	0,016	0,285	0,776

IV. Result and Discussion

Macroscopic modeling describes intersections at a low level of details[12], Like what is discussed in the article by Demir[16], speed has a significant effect on fuel consumption and optimal speed could lead to a better reduction of CO_2 emissions.

According to the articles of the following authors[5][17][18][19][20]the effect of driver behavior on diesel fuel consumption, engine types, speed and acceleration were considered as the main factors, thus transport-related CO_2 emissions are affected by various vehicle type conditions (engine power, torque, fuel type, aerodynamic drag coefficient, etc.) and the characteristics of the delivery operation (type of road, slope, vehicle speed, load, etc.)[21], psychological factors of the driver (personality traits)[22], attitudes and intentions [23]and risk taking [24]in studies dealing with fuel savings and emission reductions. In addition, other variables also affecting CO_2 emissions including traffic, driving style[25]and weather conditions [26].

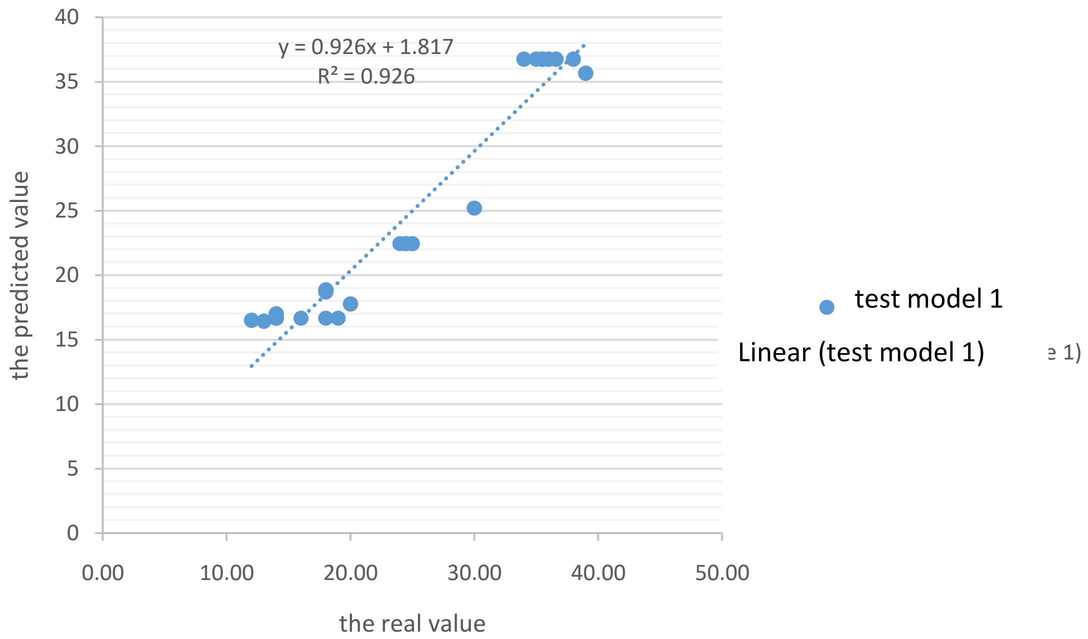

Figure2: the predicted values compared to the real values according to the model 1

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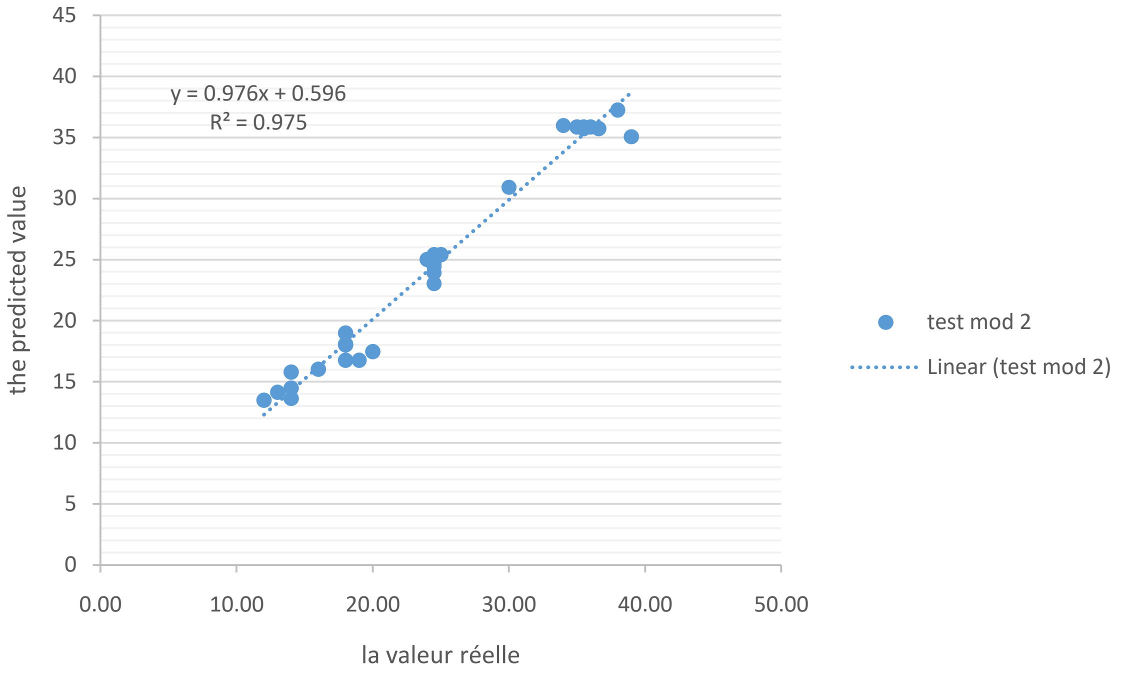

Figure 3: Predicted values versus real values by model 2

Model 1 and 2 validation were performed between the predicted regression equations for predicted consumption and measured consumption according to Figure 3 and Figure 4 (mod1 test and mod2 test). To test the regression equations, validation was performed by multiple correlation for 28 types of vehicles. From the result obtained, the regression equation predicted by Model 1 gave a strong R^2 =0, 9265, so model 2 is getting the R^2 =0, 9265to R^2 = 0, 9758, this variation of 0, 0493appears significant.

The high correlation confirmed that the predicted fuel consumption was reliable and efficient, indicating that the expected consumption of the multiple linear regression was similar, accurate and efficient, confirming that the fuel consumption predicted by the multiple linear regression was similar to the measured one.

Model 3 presents a R^2 =0, 659less than model 2 withR^2 = 0, 9758which shows that taking into consideration variables such as acceleration and speed generates noisy and unstable environmental conditions.

When comparing the fuel consumption of a quiet motorist and an aggressive driver, who drive too fast, accelerate more than necessary, brake suddenly, change gears continuously ...,we can obtain a difference up to 20% on the road and 40% in the city according to [27][28].

Model 3, is related to the type of transmission, as it was mentioned, the optimality can be achieved with an automatic transmission of speed to not leave room for unnecessary changes on the part of the driver.

This model is less controllable, that is to say the vehicle fleet manager can educate drivers by offering training for example. However, he will never be able to fully control the driving behavior on the road.

The type of driver is unfortunately not taken into account in any of the existing calculation methods because of its difficult to control a dynamic agent.

Conclusion

Regression analysis can be used for both forecasting and controlling a product or process characteristic that is essential to quality based on a set of key process parameters.

Although the use of regression analysis for prediction purposes is highly responsive, this is not the case for controlling process variables.

Sometimes, when planning a trip, it is essential to find the best route to get to the road transport network taking into account environmental conditions, condition of vehicles, driver, tonnage, destination infrastructure and schedule, which influence safety and real-time travel.

Controlled vehicles already constitute a relatively large database in which the conditions of use and operation are known in detail, In addition, these vehicles, being "in circulation", are also an excellent "sensor" for measuring traffic conditions.

Analysis of their speed profiles allowed to some extent describe driving conditions vehicle flow, taking into account the diversity of driver behavior.

The vehicle driver has a major role in minimizing the emissions recorded in the same period of traffic with the same category of vehicle, make a sustainable optimization of road transport of goods is a combination between the strategic decision of Transport Manager and an operational decision carrier.

The strategic decision is ensured by the choice of the optimal route in terms of safety, speed and cost, On the other hand the operational decision is directly related to the carrier behavior related to its responsiveness, acceleration, deceleration, braking and concentration code compliance of the road and the transmission of information to the actors of the chain when it is necessary.

Bibliography

[1] A. Shukla and M. Alum, “Assessment of Real World On-Road Vehicle Emissions under Dynamic Urban Traffic Conditions i n Delhi,” *International Journal of Urban Sciences*, vol. 14, no. 2, pp. 207–220, 2010.

[2] S. Carrese, A. Gemma, and S. La Spada, “Impacts of Driving Behaviours, Slope and Vehicle Load Factor on Bus Fuel Consumption and Emissions: A Real Case Study in the City of Rome,” *Procedia - Social and Behavioral Sciences*, vol. 87, pp. 211–221, 2013.

[3] W. Ech-chelfi and M. El Hammoumi, “Survey on the relation between road freight transport, SCM and sustainable development,” *Yugoslav Journal of Operations Research*, vol. 29, no. 2, pp. 151–176, 2019.

[4] S. M. R. Dente and L. Tavasszy, “Policy oriented emission factors for road freight transport,” *Transportation Research Part D*, 2017.

[5] N. H. Muslim, A. Keyvanfar, A. Shafaghat, M. M. Abdullahi, and M. Khorami, “Green driver: Travel behaviors revisited on fuel saving and less emission,” *Sustainability (Switzerland)*, vol. 10, no. 2, pp. 1–30, 2018.

[6] W. Ech-chelfi and M. EL Hammoumi, “Development of the Java-Based Dijkstra Algorithm for Optimal Path Detection,” *Journal of engineering and applied sciences*, vol. 14, no. 18, pp. 6620–6624, 2019.

[7] H. YUE, Huanyu et RAKHA, “Validation of the VT-Meso vehicle fuel consumption and emission model. Efficient Transportation and Pavement Systems: Characterization Mechanisms, Simulation, and Modeling,” p. 97, 2008.

[8] C. Samaras, D. Tsokolis, S. Toffolo, G. Magra, L. Ntziachristos, and Z. Samaras, “Improving fuel consumption and CO2 emissions calculations in urban areas by coupling a dynamic micro traffic model with an instantaneous emissions model,” *Transportation Research Part D: Transport and Environment*, vol. 65, no. xxxx, pp. 772–783, 2018.

[9] P. S. MANN, “Introductory statistics,” *John Wiley & Sons*, 2007.

[10] R. B. Darlington and A. F. Hayes, *Regression Analysis and Linear Models: Concepts, Application and Implementation*. 2016.

[11] W. Wisetjindawat, K. Yamamoto, and F. Marchal, “A Commodity Distribution Model for a Multi-Agent Freight System,” *Procedia - Social and Behavioral Sciences*, vol. 39, pp. 534–542, 2012.

January - February 2020
ISSN: 0193 - 4120 Page No. 376 - 386

[12] N. N. Nor Azlan and M. Md Rohani, “Overview Of Application Of Traffic Simulation Model,” *MATEC Web of Conferences*, vol. 150, p. 03006, 2018.

[13] M. Barth, T. Youngslove, and G. Scora, “Development of a heavy-duty diesel modal emissions and fuel consumption model,” *PATH Research Report*, no. January, p. 113, 2005.

[14] S. Wang, B. Ji, J. Zhao, W. Liu, and T. Xu, “Predicting ship fuel consumption based on LASSO regression,” *Transportation Research Part D: Transport and Environment*, vol. 65, no. xxxx, pp. 817–824, 2018.

[15] E. Demir, T. Bektaş, and G. Laporte, “A comparative analysis of several vehicle emission models for road freight transportation,” *Transportation Research Part D: Transport and Environment*, vol. 16, no. 5, pp. 347–357, 2011.

[16] E. Demir, T. Bektaş, and G. Laporte, “An adaptive large neighborhood search heuristic for the Pollution-Routing Problem,” *European Journal of Operational Research*, vol. 223, no. 2, pp. 346–359, 2012.

[17] J. Chung, Y. Kyung, and J. Kim, “Optimal sustainable road plans using multi-objective optimization approach,” *Transport Policy*, vol. 49, pp. 105–113, 2016.

[18] E. Demir, T. Bektas, and G. Laporte, “A review of recent research on green road freight transportation,” *European Journal of Operational Research*, 2014.

[19] M. Baumgartner, J. Léonardi, and O. Krusch, “Improving computerized routing and scheduling and vehicle telematics: A qualitative survey,” *Transportation Research Part D: Transport and Environment*, vol. 13, no. 6, pp. 377–382, 2008.

[20] W. Ech-chelfi and M. El Hammoumi, “The Impact Level of the Environmental Approach on Moroccan Industries: Case Study,” *International Journal of Engineering Research and Technology*, vol. 12, no. 2, pp. 172–179, 2019.

[21] R. Akçelik and M. Besley, “Operating cost , fuel consumption , and emission models in aaSIDRA and aaMOTION,” *ResearchGate*, no. March 2014, 2003.

[22] D. Jovanović, K. Lipovac, P. Stanojević, and D. Stanojević, “The effects of personality traits on driving-related anger and aggressive behaviour in traffic among Serbian drivers,” *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 14, no. 1, pp. 43–53, 2011.

[23] F. Lucidi, L. Mallia, L. Lazuras, and C. Violani, “Personality and attitudes as predictors of risky driving among older drivers,” *Accident Analysis and Prevention*, vol. 72, pp. 318–324, 2014.

[24] X. Cai, J. J. Lu, Y. Xing, C. Jiang, and W. Lu, “Analyzing Driving Risks of Roadway Traffic under Adverse Weather Conditions: In Case of Rain Day,” *Procedia - Social and Behavioral Sciences*, vol. 96, no. Cictp, pp. 2563–2571, 2013.

[25] Alan McKinnon, Sharon Cullinane, M. Browne, and A. Whiteing, *Greenn Logistics: Improving the environmental sustaintability of logistics*. 2010.

[26] C. Kohn, *Centralisation of distribution systems and its environmental effects*, no. 91. 2005.

[27] A. A. de l’Environnement et de la M. de L’Energie, “CONSOMMATIONS CONVENTIONNELLES DE CARBURANT ET ÉMISSIONS DE CO2,” *Guide édité en application du décret no 2002-1508 du 23 décembre 2002, relatif à l’information sur la consommation de carburant et les émissions de dioxyde de carbone des voitures particulières neuves.*, p. 353, 2018.

[28] M.-P. Trépanier and L. C. Coelho, “Facteurs et méthodes de calcul d’émissions de gaz à effet de serre,” *Centre interuniversitaire de recherche sur les réseaux d’entreprise, la logistique et le transport(CIRRELT)*, 2017.