International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2024, 14(1), 603-611.

Forecasting Petroleum Products Consumption in the Chadian Road Transport Sector using Optimised Grey Models

Ahmat Khazali Acyl[1], Flavian Emmanuel Sapnken[1,2,3]*, Aubin Kinfack Jeutsa[4], Jean Marie Stevy Sama[2], Marcel Rodrigue Ewodo-Amougou[2], Jean Gaston Tamba[1,2,3]

[1]Transports and Applied Logistics Laboratory, University Institute of Technology, University of Douala, PO Box 8698 Douala, Cameroon, [2]Laboratory of Technologies and Applied Science, PO Box 8698, IUT Douala, Douala, Cameroon, [3]Energy Insight-Tomorrow Today, PO Box 2043 Douala, Cameroon, [4]Higher Technical Teachers' Training College, University of Buea, Buea, Cameroon. *Email: sapnken.emmanuel@gmail.com

Received: 28 July 2023 **Accepted:** 20 December 2023 **DOI:** https://doi.org/10.32479/ijeep.14828

ABSTRACT

This study aims to estimate the demand for petroleum products (PP) in the Chadian road sector by 2030 and to determine which of the two models used is the most efficient. The methodology is based on two optimised Grey models, namely: The Sequential-GM (1,N)-GA and NeuralODE-GM (1,1) models. These models reduce forecasting errors compared with the conventional Grey model. The forecasts confirm that both models are robust, with MAPEs of 1.16% and 2.5% respectively for gasoline and diesel obtained with the Sequential-GM (1,N)-GA, and 3.3% and 4.8% respectively for gasoline and diesel obtained with the NeuralODE-GM (1,1). We note that the Sequential-GM (1,N)-GA is more robust than NeuralODE-GM (1,1) with regard to MAPEs. The estimated consumption needs for gasoline and diesel in the road transport sector by 2030 are 294376818.5 and 381570061.5 litres respectively for the Sequential-GM (1,N)-GA and 264376818.5 and 375570061.5 litres for the NeuralODE-GM (1,1). Based on these results, securing the supply of PP in the road transport sector requires the development of the downstream petroleum sector. The development of alternative energies and the acquisition of hybrid vehicles. A policy encouraging mass transport in urban areas can considerably reduce energy consumption in this sector. This study adds to the literature through the simultaneous use of two new optimised grey models and their comparison in terms of predicting demand for PP in the Chadian road transport sector.

Keywords: Forecasting, Petroleum Products, Road Transport, Grey Models, Chad
JEL Classifications: Q4, Q47

1. INTRODUCTION

The road transport sector covers a wide range of operations related to the mobility of people and goods, and therefore has a significant impact on a country's economy (Sahraei and Çodur, 2022). However, it is one of the main users of fossil fuels and contributes to environmental degradation (Zhang et al., 2009; Javanmard et al., 2023). As a result of increasing energy use and demand in the road transport sector, many countries are experiencing major difficulties in securing energy supplies (Sapnken et al., 2017; Tamba et al., 2017; Sapnken et al., 2020; Javanmard et al., 2023).

1.1. Background

The transport sector in Chad accounts for a large proportion of petroleum product consumption. For example, in 2011, the transport sector was the largest consumer of petroleum products (PP), accounting for over 67% of overall consumption, ahead of the industrial sector (17%), with the residential and tertiary sectors accounting for the remaining 16% (Richard, 2014). This transport sector is dominated by road transport, which has seen an expansion of its road network over the period 2000-2019, from 350 km to 2300 km of asphalt road, and accounts for more than 95% of national and international trade (BID, 2023).

Road transport in Chad has also seen an increase in the consumption of PP, particularly gasoline and diesel. Between 2008 and 2019, gasoline consumption rose from 25 ktoe to 196 ktoe in 2019, while diesel consumption rose from 87 ktoe to 317 ktoe (Figures 1 and 2). Over the coming years, this trend could increase further for the following reasons: (i) Energy consumption and the expansion of the transport sector are closely linked, so the more transport there is, the more energy is consumed. (ii) Through its Vision 2030, Chad has made the development of road infrastructure one of its key planks in supporting economic growth. However, the expansion of economic growth leads to an increase in the transport of goods and services by road over greater distances, which in turn leads to an increase in energy consumption. (iii) Chad is one of the least urbanised countries in the world, yet it has experienced strong and uncontrolled urbanisation in recent years (TCNTCC, 2020). On a national scale, the urban population has risen from <10% of the total population in 1960 to 30% in 2010, and then to 32% today (TCNTCC, 2020). This strong urbanisation could develop an appetite for energy consumption in all sectors of activity, particularly the road transport sector.

Chad could therefore be faced with the issue of the supply of PP for the road transport sector as a result of the country's rapid urbanisation, expanding economic growth, the construction of road transport infrastructure and booming industrialisation. It is therefore crucial that the government of Chad studies the driving forces behind the use of PP in the transport sector. To ensure a secure supply of PP in the road transport sector, and to avoid any distortion of economic expansion as envisaged in Vision 2030, long-term forecasts are important to assess the demand for PP in Chad.

Forecasting the consumption of PP in the road sector in Chad is also of the utmost importance. Chad covers an area of 1,284,000 km², and inter-city transport relies almost entirely on roads, in the absence of railways and river transport. Such a forecasting study could enable the government of the Republic of Chad to better develop future strategies for the storage and management of petroleum product consumption, in order to avoid any disruption in the supply of PP.

1.2. Related Studies

Numerous studies have focused on forecasting the consumption of PP, and there are a multitude of forecasting techniques to be found in the literature (Tamba et al., 2018). Among these techniques, those known as grey (GM) stand out from all the others. Indeed, as pointed out by Sapnken and Tamba (2022). GMs are very simple to understand and offer several advantages, namely: They only require a minimum of four observations, there is no need to make overly onerous assumptions about the nature of these observations, and GMs are capable of making very accurate forecasts (Sapnken, 2023). For example Chen et al. (2021) who adopted a single-variable Grey fractional forecasting model to forecast the consumption of diesel, heavy fuel oil, gasoline, coal and natural gas in the Beijing-Tianjin-Hebei region of China. Wang and Cao (2021) study the forecasts of energy consumption, economic growth, and urbanization from 2020 to 2025 through the multivariate grey models SRMGM (1,N) and BRMGM (1,N). The estimates show that future energy consumption in the transport sector will experience an upward trend from 2020 to 2025. The Grey GM model (1,1) was used by Lu et al. (2009) to analyse the growth trends in the number of motor vehicles, vehicle energy usage, and CO_2 emissions in Taiwan's road transportation sector from 2007 to 2025. The results show an increasing trend in the number of vehicles, vehicle energy consumption and CO_2 emissions in the road transport system, with respective annual growth rates of 3.64%, 3.25% and 3.23% over the next 18 years.

In some cases, GM models fail to produce forecasts with the desired accuracy. When this is the case, we can either use optimisation algorithms, such as machine learning (Sapnken et al., 2023c) optimise predictions using heuristic algorithms (Sapnken et al., 2023a, 2022a) or restructure the functional prediction model (Sapnken and Tamba, 2022). As an example, Sonmez et al. (2017) predicted Turkey's transport energy needs over the period 2014-2034, using the ABC algorithm across different variables such as total annual vehicle-km, population and gross domestic product. The forecast results show an increase in energy consumption in the transport sector in Turkey until 2034. Teng et al. (2017) forecast energy consumption in China's transport sector using a cluster data processing model (CDPM) and a combination of the variables GDP, urbanisation, GNI and turnover. The results show that, according to the scenarios, China's transport is anticipated to use up around 622,048 MTCE in 2041 and then gradually decline. Fani and Norouzi (2020) estimated gasoline consumption for Teheran's transports through a multi-layer neural network, based on social and economic indicators on a 2010-2016 basis. The prediction results showed that if the descriptive variables' current trend continues, the consumption pattern in the transport sector would increase over the next few years. Chai et al. (2012) analyse the consumption of PP (mainly gasoline and diesel) in the transportation sector in China using Bayesian linear regression theory and Marko Chain Monte Carlo method. Using historical data covering the period from 1985 to 2009, the forecast results suggest an increase in gasoline and diesel consumption in China's transport sector. Azariah (2015) predicts the future demand for PP in Malaysia's transport sector with Artificial Neural Network (ANN) and using GDP, number of registered cars, imports and exports as inputs using Artificial Neural Network (ANN). The results obtained for the years 2020, 2025 and 2035 are 559.44, 581.779 and 609.41 ktoe respectively. The author calls on the Malaysian authorities to develop new policies relating to oil consumption in the transport sector.

Although there are other forecasting models in the literature, grey models (uni or multivariate, and even hybrid) and optimisation heuristics are among the most widely used because of their effectiveness and simplicity. In addition, the studies mentioned above show that a combination of several variables such as the urbanisation rate, the energy price, the goods turnover rate, the distance travelled by vehicles, the vehicle fleet and the per capita income have been used as input data.

1.3. Objectives, Contribution and Work Organisation

This article uses the Sequential-GM (1,N)-GA (Sapnken et al., 2022b) and NeuralODE-GM(1,1) (Sapnken et al., 2023b) to estimate the future consumption of road transport gasoline and diesel needs in Chad for the period 2020-2030. The two models are compared based on their respective accuracies in order to of the selected models are assessed in the context of the projected demand for PP in the road transport sector in Chad up to 2030, the year of emergence. The contribution of this article is therefore to provide Chadian policy-makers with guidelines that will make it possible to establish an effective and judicious policy for energy use in the transport sector, and more specifically in the road transport sector.

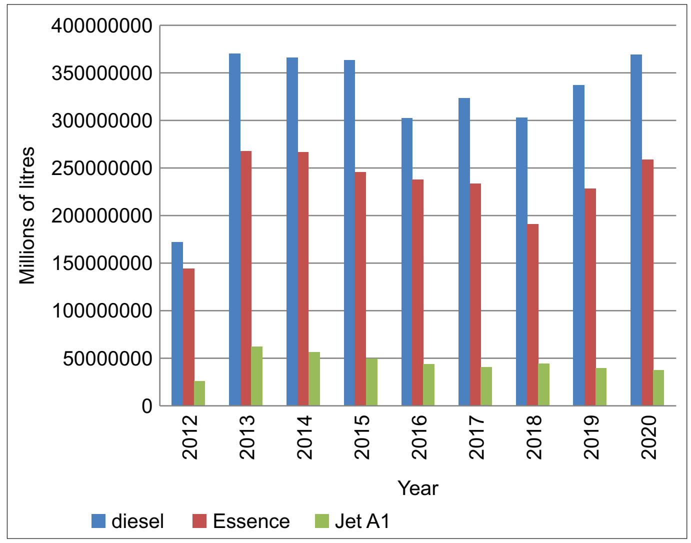
In order to achieve the objective of this study, it is useful to begin by providing an overview of the Chadian oil sector (Section 2). An overview of the methods used is provided in Section 3. Section 4 presents the results and related discussion, while Section 5 highlights the conclusions and looks ahead to future work.

2. BRIEF OVERVIEW OF THE CHADIAN OIL SECTOR

Oil was discovered in Chad in the 1970s, but its exploitation was long delayed due to the various expressions of civil war in the country, which discouraged its exploration and use (FMI, 2016). It was in 2003 that Chad achieved the status of a producing country, with average production of 200,000 barrels/day in the southern region of the Doba basin (Augé, 2011). Crude oil production peaked in 2004 at 225,000 barrels/day, putting Chad on a par with oil-producing countries such as Sudan, Gabon and Congo (Massuyeau and Dorbeau-Falchier, 2005). The installation of a pipeline over a thousand kilometres long has enabled crude oil to be exported to the south of Cameroon (Augé, 2011). To meet the demand for PP, the Chadian government is going to refine part of its crude oil production.

The crude oil refining industry in Chad began in 2003 with the commissioning of the Société de Raffinage de N'Djaména (SRN). SRN is 60% owned by China National Petroleum Corporation International (CNPCI) and 40% by Chadians through the "Société d'Hydrocarbure au Tchad" (IMF, 2016). SRN has an oil refining capacity of 20,000 barrels of oil (Augé, 2011). SRN's mission is to exploit and refine crude oil from Chad's production fields, in order to supply the country with PP and substantially reduce imports of products such as butane, gasoline, jet, paraffin, diesel, distillate and fuel oil from neighbouring countries (Cameroon, Nigeria, Libya and Sudan). In addition to the supply of PP refined in Chad, there are counter-trade products from other neighbouring countries, which affect SRN's profitability. Figure 1 shows the evolution of PP from SRN's production. It shows that diesel and petrol production peaked in 2013, followed by a general decline in petroleum product production until 2018. Finally, from 2018 to 2020, there is an increasing trend in the production of PP, particularly gasoline and diesel. This variation in the production of these two PP at SRN is probably due to movements in Chad's economic environment. For example, the subsidy on PP at the start of SRN's operations, the drop in crude oil production and the work to expand the refinery.

Figure 1: Trend in Société de Raffinage de N'Djaména's production of PP



The oil industry is developed by the Ministry of Petroleum and Energy. It is responsible for implementing, designing, coordinating, monitoring and controlling government policy. The Société Hydrocarbure du Tchad (SHT) is responsible for monitoring activities in the upstream and downstream petroleum sectors (SHT, 2023). In the upstream sector, SHT is responsible for promoting the development, exploration, production, piping and transportation of liquid and gaseous hydrocarbons (SHT, 2023).

In the downstream sector, SHT is responsible for developing storage and distribution capacity for PP. The Autorité de Régulation du Secteur Pétrolier Aval du Tchad (ARSAT) is responsible for overseeing regulation, control and compliance with standards, as well as the operations of oil and gas operators and producers. In addition to SHT, there are a number of private companies operating in the upstream and downstream sectors, including Total Marketing Chad, Libya Oil Chad, Société des Produits Pétroliers, ALMANNA, Société Pétrolière et des Transports, CNPCI, ESSO Chad and Tradex Cameroon.

The different PP that can be found on the oil market are: Jet A1, diesel, essential oil, paraffin and LPG (Richard, 2014). These different PP are served in the market through marketers so there are more than 72 (ARSAT, 2022). When these various PP are made available to marketers, they are supplied to end consumers by service stations. Today, Chad has more than 255 service stations selling these different PP in the country's 32 towns. The city of N'Djamena has the most service stations, with more than 155, or more than half of the country's total (ARSAT, 2022). The town of Abeché comes second with a total of 25 service stations, Moundou comes third with 22 service stations, and the rest of the towns share the remaining 53 stations, meaning that more than 83% of sales outlets are concentrated in the major towns.

The average monthly fuel consumption for land transport between 2007 and 2016 was 30 L/month for motorbikes, 100 L/month for light vehicles using gasoline, 100 L/month for light vehicles using gas, and 150 L/month for heavy vehicles using gas (TCNTCC, 2020) as shown in Figure 3. Light goods vehicles running on diesel were in first place in terms of fuel consumption over the period 2007-2016, followed by motorbikes. Light goods vehicles come third in terms of gasoline consumption. Finally, heavy goods vehicles running on diesel come last in terms of energy consumption (TCNTCC, 2020).

The prices of PP at the pump are regulated by ARSAT. Before the Djeramaya refinery was commissioned, the prices of PP at the pump were around 650 FCFA per litre for gasoline and diesel (Richard, 2014). When the refinery came on stream in 2011, petrol and diesel prices fell from CFAF 650 to CFAF 374 and CFA 330 per litre respectively (Richard, 2014). A few years later, the various prices of PP were readjusted and increased to CFAF 525 for diesel and CFAF 480 for petrol. However, the prices of PP fixed at the pump differ from one town to another. The reference prices for PP are those charged in the capital, N'djamena. For other localities, a transport margin is applied, which varies between 30 and 170 FCFA depending on the distance between the refinery and the service area (ARSAT, 2022).

Faced with an upward trend in the consumption of PP in general, and in the road transport sector in particular, Chad's emergence project for 2030, which requires greater energy consumption on the one hand, and declining reserves and production of crude oil on the other, could mean that Chad is faced with a challenge in terms of security of energy supply. In such a context, it is necessary to estimate the demand for PP in the road transport sector in order to provide the government of Chad with more information and facilitate decision-making in terms of planning and management of petroleum product consumption in the road transport sector.

3. METHODS AND DATASETS

3.1. The Sequential GMC (1,N) Model

There are six basic steps to generate the GMC (1,n) model (Shen et al., 2021; Tien, 2012):

3.1.1. Step (i): Define the input sequences

Consider that $X_1^{(0)}, X_2^{(0)}, \supset, X_n^{(0)}$ represent nonnegative sequences variables (with $X_1^{(0)}$ being the output and $X_i^{(0)}, i = 2,3,\ldots,n$ are the input variables). Each of this sequence is defined by Eq. (1):

$$X_i^{(0)} = \left\{x_i^{(0)}(1), x_i^{(0)}(2), \ldots, x_i^{(0)}(k)\right\}; i = 1,2,\ldots,n; k \geq 4 \quad (1)$$

Here, the superscript (0) is used to represent the raw data.

3.1.2. Step (ii): Generate the 1st order cumulative raw sequence

The raw sequence $X_i^{(0)}$ undergoes the first order accumulated generation operation (1-AGO) to yield $X_i^{(1)}$ as defined in Eqs. (2) and (3):

$$X_i^{(1)} = \left\{x_i^{(1)}(1), x_i^{(1)}(2), \ldots, x_i^{(1)}(k)\right\} \quad (2)$$

Where:

$$x_i^{(1)}(h) = \sum\nolimits_{g=1}^{h} x_i^{(0)}(g); h = 2,3,\ldots,T \quad (3)$$

Here, the superscript (1) represents 1-AGO sequences. We can note here that is monotonous sequence (Hamzacebi and Es, 2014a).

3.1.3. Step (iii): Calculate the system's background value

This is done with Eq. (4) as follows:

$$Z_1^{(1)}(h) = \theta X_1^{(1)}(h) + (1-\theta) X_1^{(1)}(1-h); h = 2,3,\ldots,T \quad (4)$$

θ $(0 < \theta < 1)$ represents the horizontal adjustment coefficient (Ding et al., 2018; Hamzacebi and Es, 2014a).

3.1.4. Step (iv): Designing the system of Grey equations

By creating a connection between output and input sequences, the grey system is trained:

$$dx_1^{(1)}(h)/dh + ax_1^{(1)}(h) = b_2 x_2^{(1)}(h) + b_3 x_3^{(1)}(h) + \cdots + b_n x_n^{(1)}(h) + u \quad (5)$$

The grey input coefficients are $b_{j=1},\ldots,n$ the development coefficient is a, and the GMC(1,n) parameter is u (Bahrami et al., 2014; Deng, 1982; Ding et al., 2018; Hamzacebi and Es, 2014a). The right side of Eq. (5) is described by Tien (2012) as a function $f(h)$. Then, after integrating both sides of Eq. (5) from h–1 to h using the trapezoid method, Eq. (5) is roughly represented by the following difference equation (Tien, 2012):

$$x_1^{(0)}(h) + az_1^{(1)}(h) = b_2 z_2^{(1)}(h) + b_3 z_3^{(1)}(h) + \cdots + b_n z_n^{(1)}(h) + u \quad (6)$$

Eq. (6) may thus be thought of as a system of linear equations with respect to the coefficients of matrix $A = \left[ab_2 b_3 \ldots b_n u\right]^T$. By using the least squares approach, these coefficients are determined (Bahrami et al., 2014; Deng, 1982; Ding et al., 2018; Hamzacebi and Es, 2014a). Thus, the matrix A are calculated using least squares as given in Eq. (7):

$$A = \left[ab_2 b_3 \ldots b_n u\right]^T = (B^T B)^{-1} B^T Y \quad (7)$$

Here: $B = \begin{pmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & x_3^{(1)}(2) \ldots x_n^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & x_3^{(1)}(3) \cdots x_n^{(1)}(3) \\ \vdots & \vdots & \vdots \ddots \vdots \\ -z_1^{(1)}(n) & x_2^{(1)}(n) & x_3^{(1)}(n) \cdots x_n^{(1)}(m) \end{pmatrix}$; and

$$Y = \begin{pmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(n) \end{pmatrix}$$

3.1.5. Step (v): Solving the system's differential equation

Eq. (5)'s solution is:

$$\hat{x}_1^{(1)}(h) = x_1^{(0)}(1) e^{a(1-h)} + \int_1^h e^{a(\tau - h)} f(\tau) d\tau; \quad h \geq 2 \quad (8)$$

Its value is only approximable by numerical techniques due to the existence of the convolution integral. Eq. (8) changes to Eq. (9) using the trapezoid formula.

$$\hat{x}_1^{(1)}(h) = x_1^{(0)}(1)e^{a(1-h)} + 0.5k(h)$$
$$\sum_{i=2}^{n}\left[f(\tau)e^{a(\tau-h)} + f(\tau-1)e^{a(\tau-h-1)}\right];\ t \geq 2 \tag{9}$$

In Eq. (9), $h(t)$ is defined as: Recall that $\hat{x}_1^{(1)}(1) = x_1^{(0)}(1)$. $k(h) = 0$ if $h < 2$ then $k(h) = 1$

3.1.6. Step (vi): Inverse accumulated generation operation (IAGO)

The projected values of $\hat{x}_1^{(0)}(h)$ are then produced using IAGO and are displayed in Eq. (10):

$$\hat{x}_1^{(0)}(h) = \hat{x}_1^{(1)}(h) - \hat{x}_1^{(1)}(h-1); \qquad h \geq 2 \tag{10}$$

In terms of quality, GMC (1,N) is a major upgrade over GM (1,N). However, (Shen et al., 2021) have shown that it contains a number of glaring faults. It was shown in references (Ding et al., 2017; Hamzacebi and Es, 2014b; Tseng et al., 2001) that k, θ, a and $b_{j=1},\ldots,n$ have an impact on the precision of GMs. The complete procedure is demonstrated by (Sapnken et al., 2022a). Readers can refer to it for more details. Here, we have just summarised the essential steps.

3.2. The NeuralODE-GM (1,1) Model

NeuralODE-GM (1,1) substitutes a function $f(x^{(1)}(h),h,\psi)$ for the gradient of the 1-AGO sequence when parameterizing the differential model in place of OLS (Cui et al., 2009). Thus, it may appear that the grey image equation (Eq. [4]) is a neural ODE, and by honing its ODE, a more precise prediction model may be created. Eq. (11) gives the function $f(x^{(1)}(h),h,\psi)$.

$$f\left(x^{(1)}(h),h,\psi\right) = \sum_{i=1}^{n}\psi_i g\left(x^{(1)}(h),h\right) \tag{11}$$

Consequently, it is possible to think of $f\left(x^{(1)}(h),h,\psi\right)$ as a linear sequence of transformations between $x^{(1)}(h)$ and h. Similar to this, an RN may be seen as a succession of input transformations. We can discover an approximation of the function f using $x^{(1)}(h)$ as RN inputs. The equation for the image of NeuralODE-GM (1,1) is expressed as follows by setting $l(h) = x^{(1)}(h)$:

$$\nabla_t l(h) = \frac{dl(h)}{dh} = f\left(l(h),h,\psi\right) \tag{12}$$

To create a homogeneous, heterogeneous, linear, or nonlinear model, one can modify the RN that specifies the function f. The anticipated sequences $\hat{X}^{(0)}$ must be calculated by the ODEsolver using the initial conditions $l(0)$, ψ and the time span $tspan = [0,1, 2,\ldots, n-1]$ as follows:

$$\begin{cases} \hat{X}^{(1)} = \left\{l(0),\hat{l}(1),\hat{l}(2),\ldots,\hat{l}(n-1)\right\} \\ = ODEsolver\left[l(h),h,f\left(l(h),h,\psi\right),l(0),tspan,\psi\right] \end{cases} \tag{13}$$

As the objective function, we employ the loss function Δ defined in Eq. (14). This function will be used in order to optimize the parameter values ψ.

$$\Delta = \sum_{h=0}^{n}(l(h)-\hat{l}(h))^2 = \hat{X}^{(1)} - X^{(0)2}_{2} \tag{14}$$

In real-world applications, one starts by feeding the neural ODE the required interval and beginning circumstances. The predictive sequence, which is determined by the latter and, in principle, is the same length as the desired interval. After that, using the expected sequence, we create the loss function. The gradient descent technique (Eq. [15]) is used to update the parameters ψ:

$$\psi^{t+1} = \psi^{t} - \eta\frac{d\Delta}{d\psi} \tag{15}$$

Here, the calculation step is t and the descending step is η. The fact that $\frac{\partial f\left(l(h),h,\psi\right)}{\partial l(h)}$ and $\frac{\partial f\left(l(h),h,\psi\right)}{\partial \psi}$ is an RN necessitates some changes. Given that f cannot be calculated directly, the derivative rule given below must be applied:

$$\frac{\partial f\left(l(h),h,\psi\right)}{\partial l(h_j)} = \frac{\partial f\left(l(h),h,\psi\right)}{\partial l(h_{n-1})}\prod_{j=n-1}^{i+1}\frac{\partial l(h_j)}{\partial l(h_{j-1})} \tag{16}$$

$$\frac{\partial f\left(l(h),h,\psi\right)}{\partial \psi_j} = \frac{\partial f\left(l(h),h,\psi\right)}{\partial l(h_{n-1})}\prod_{j=n-1}^{i+1}\frac{\partial l(h_j)}{\partial \psi(h_{j-1})} \tag{17}$$

These equations refer to the j-th layer's output values and parameters, respectively, as $l(h_j)$ and ψ_j. We compute the original sequences provided by Eq. (18) after getting $\hat{X}^{(1)}$:

$$\hat{x}^{(0)}(h) = \hat{x}^{(1)}(h) - \hat{x}^{(1)}(h-1), \qquad h \in [1, n-1] \tag{18}$$

Eq. (19) is used to implement the NeuralODE-GM (1,1)'s grey prediction model.

$$\hat{x}^{(0)}(h+1) = \hat{x}^{(1)}(h+1) - \hat{x}^{(1)}(h), \qquad e \geq n \tag{19}$$

In the works of (Sapnken et al., 2023b), the procedural algorithm of NeuralODE-GM (1,1) is presented as well as all related demonstrations.

3.3. Datasets

In order to be able to implement the two models with a view to forecasting the consumption of petroleum products in the Chadian road sector, we used the necessary data collected from approved institutions. Specifically, we collected data on actual diesel and gasoline consumption, as well as their respective prices, from

Figure 2: Trends in diesel and gasoline consumption

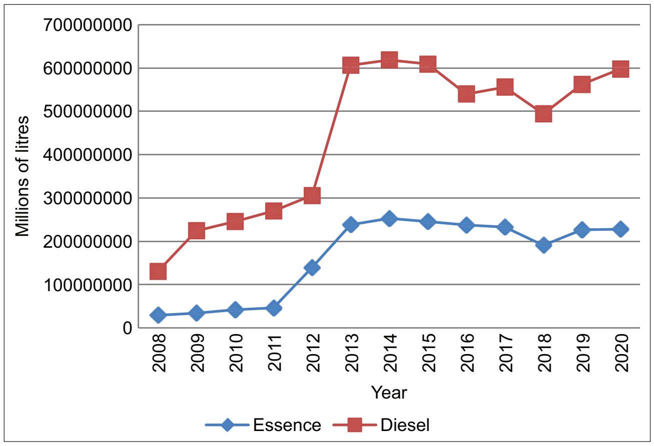
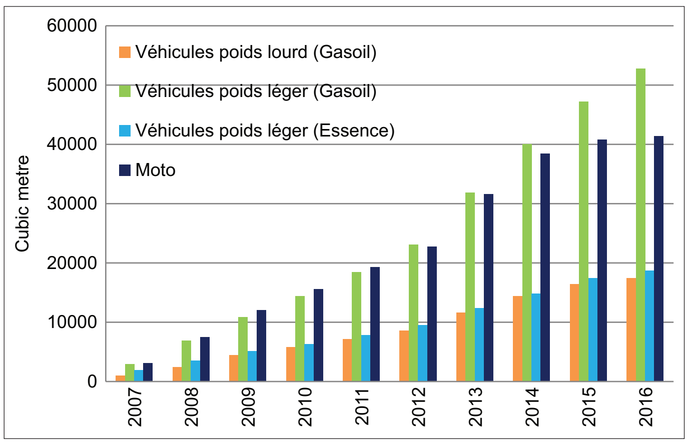


Figure 3: Diesel and gasoline consumption trends for road transport (TCNTCC, 2020)



ARSAT. All data were crosschecked with SHT data to eliminate any inconsistencies. The data collected covers the period from 2008 to 2019.

To ensure the reliability of the results, we divided the data into two groups: The training group and the validation group. The training group runs from 2008 to 2015, while the test group runs from 2016 to 2019. Dividing the data in this way prevents any leaks. Therefore, the models are trained on one group of data and we test their performance on the second, which is hidden.

4. RESULTS AND DISCUSSION

4.1. Simulation Results and Model Robustness

Chad intends to achieve its goal of emerging as a stable economic society by 2030. Based on this objective, the results for the demand for PP (gasoline and diesel) in the road transport sector for the Sequential-GM (1,N)-GA and NeuralODE-GM(1,1) models are presented below. However, the reliability of the results depends on the validation criteria presented in Table 1. p is the number of explanatory variables, $X_1(t)$ represents actual consumption for the year, $\hat{X}_1(t)$ is the predicted consumption for the year t; N is the sample size $sd(\hat{X}_1)$ and $sd(\hat{X}_1)$ represents the standard deviation of X_1 and respectively $\hat{X}_1$. Among these different criteria, the measurement criterion par excellence is MAPE.

Table 2 shows the performance of the Sequential-GM (1,N) and NeuralODE-GM (1,1) diesel and gasolinedemand forecasting models. Table 2 shows that the Sequential-GM (1,N) and NeuralODE-GM (1,1) models perform very well in predicting energy demand in the road transport sector in Chad, with

Table 1: Precision measures and thresholds (Hamzacebi and Es, 2014c; Özmen et al., 2018; Sapnken et al., 2022b)

Criteria	Formulas	Threshold levels			
		1st (mediocre)	2nd (acceptable)	3rd (good)	4th (perfect)
R^2_{adj}	$1-\frac{N-1}{N-P-1}(1-\frac{\sum_{t-1}^{n}(X_1(t)-\hat{X}_1(t))^2}{\sum_{t-1}^{n}\left(X_1(t)-\overline{X_1}(t)\right)^2})$	<0.90	≥0.90	≥0.95	≥0.98
R^2	$\frac{1}{N-1}\sum_{t=1}^{N}\frac{(X_1(t)-\overline{X_1})(\hat{X}_1(t)-\overline{\hat{X}_1(t)}}{\sqrt{sd(X_1)^2 sd(\hat{X}_1)^2}}$	<0.90	≥0.90	≥0.95	≥0.98
MAPE	$\frac{1}{N-1}\sum_{t=1}^{N}\frac{(X_1(t)-\overline{X_1})(\hat{X}_1(t)-\overline{\hat{X}_1(t)}}{\sqrt{sd(X_1)^2 sd(\hat{X}_1)^2}}$	>0.1	≤0.1	≤0.05	≤0.01

Table 2: Predictive performance of Sequential-GM (1, N) and NeuralODE-GM (1,1) using gasoline and diesel data

Criteria	Gasoline consumption data		Diesel consumption data	
	Sequential-GM (1, N)	NeuralODE-GM (1,1)	Sequential-GM (1, N)	NeuralODE-GM (1,1)
R^2	0.99	0.99	0.98	0.98
R^2_{adj}	0.99	0.99	0.96	0.96
MAPE (%)	1.16	3.3	2.5	4.8

Table 3: Forecast demand for gasoline and diesel over the period 2020-2030

Year	Gasoline consumption (litres)		Diesel consumption (litres)	
	Sequential-GM (1, N)-GA	NeuralODE-GM (1,1)	Sequential-GM (1, N)-GA	NeuralODE-GM (1,1)
2020	230829072.5	220829072.5	345332350.5	365332350.5
2021	241183847.1	221183847.1	354956121.6	364956121.6
2022	241538621.7	231538621.7	354579892.7	374579892.7
2023	251893396.3	231893396.3	354203663.8	384203663.8
2024	252248170.9	232248170.9	363827434.9	373827434.9
2025	262602945.5	242602945.5	353451206	370451206
2026	252957720.1	262957720.1	363074977.1	389074977.1
2027	263312494.7	253312494.7	372698748.2	365698748.2
2028	283667269.3	243667269.3	372322519.3	363322519.3
2029	284022043.9	254022043.9	371946290.4	387946290.4
2030	294376818.5	264376818.5	381570061.5	375570061.5

Figure 4: Fit curves and residuals obtained with (a) S-GM (1,N), (b) NODE-GM (1,1) with premium fuel data

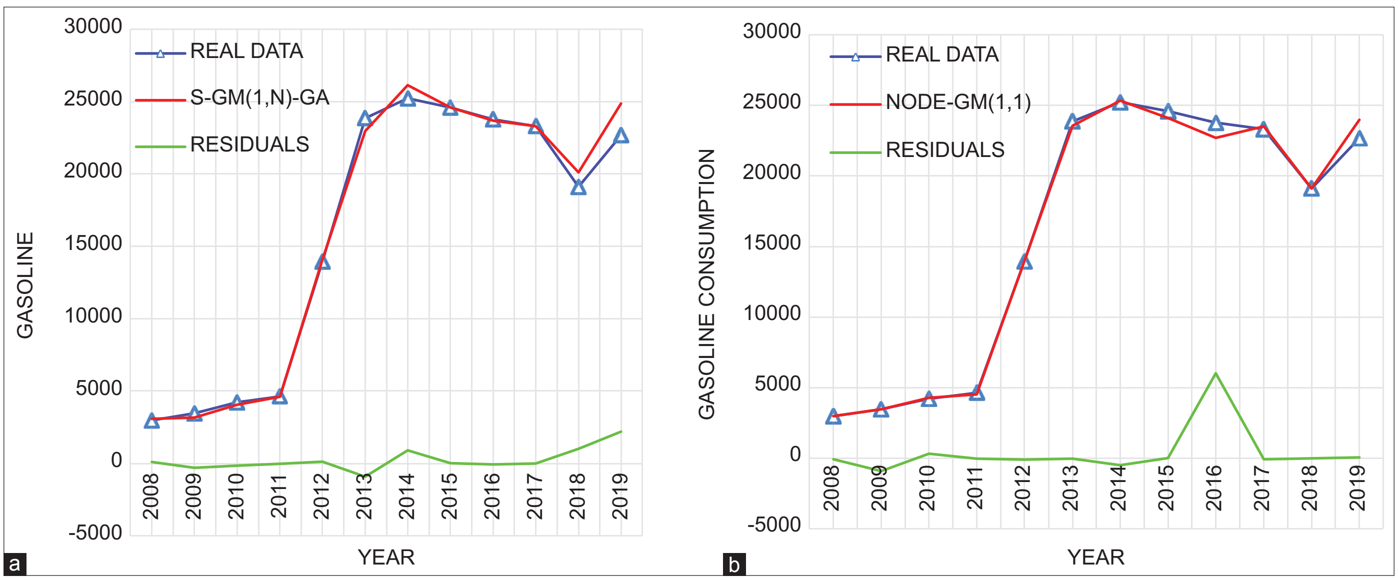
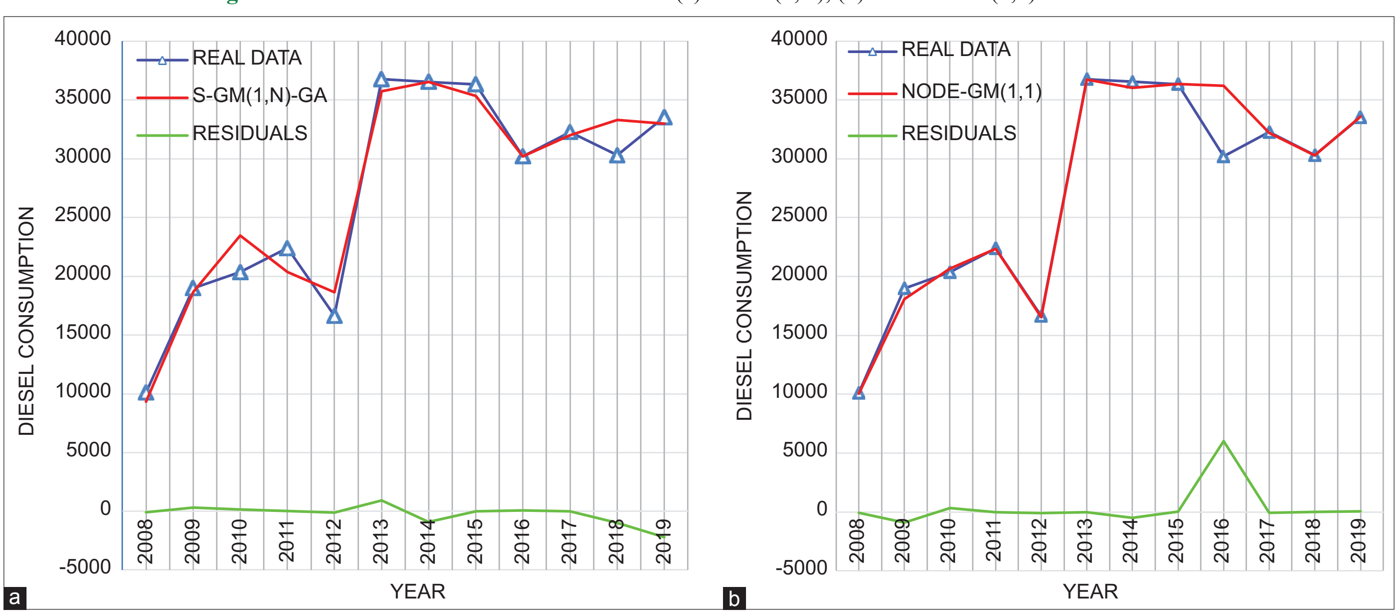


Figure 5: Fit curves and residuals obtained with (a) S-GM (1,N), (b) NODE-GM (1,1) with diesel data



correlation and determination coefficients above 96%. In addition, the Sequential-GM (1,N) and NeuralODE-GM (1,1) models have a MAPE of <5%, indicating that the error made when using a predicted value is <5%. In addition to the MAPE, Figures 4 and 5 below shows that the actual data and the predicted data are almost identical, which adds further weight to the quality of the models' performance in terms of accuracy. The Sequential-GM (1,N) model performs better than the NeuralODE-GM (1,1) model. The Sequential-GM (1,N) model has a MAPE that is lower than that of the NeuralODE-GM (1,1) model, so the Sequential-GM (1,N) model makes fewer errors when used than the NeuralODE-GM (1,1) model.

4.2. Diesel and Gasoline Demand Forecasts

The results of the estimates of demand for gasoline and diesel in the road transport sector, presented in Table 3, show that consumption of the two PP (gasoline and diesel) in the road transport sector will increase. For the Sequential-GM (1, N) model, demand for gasoline and diesel in 2030 is estimated at 294376818.5 and 381570061.5 million litres respectively. For the NeuralODE-GM (1,1) model, gasoline and diesel demand is estimated at 264376818.5 and 375570061.5 million litres respectively.

5. CONCLUSION AND POLICY IMPLICATIONS

The future energy consumption of a given transport sector can be difficult to predict and is often very complex (Pukšec et al., 2013). This paper models future petroleum product consumption in the road transport sector using Chad as a case study. The contribution of this paper is to model the demand for PP in the road transport sector using the NeuralODE-GM (1,1) and Sequential-GM (1,N) models and to compare the performance of these two models. These two models are used in order to obtain forecasting results that are reliable with regard to the size of the data used. The study chooses the Chadian road transport sector as a case study among other transport sectors because the road transport sector is one of the sectors that uses a substantial amount of final energy. The diesel and gasoline consumption models were built from training datasets covering the period 2008-2019. The results of the MAPE, correlation coefficient and determination show that the NeuralODE-GM (1,1) and Sequential-GM (1,N) models perform very well in predicting energy demand in the road sector and are competitive with other forecasting models. The hybrid Sequential-GM (1,N) model is more accurate in terms of predictive precision than the NeuralODE-GM (1,1) model.

Using Sequential-GM (1,N) and NeuralODE-GM (1,1), the demand for gasoline and diesel in the road transport sector is estimated for the period 2020-2030. The estimates from both models show an increase in demand for gasoline and diesel in the transport sector over this period. These estimates serve as a reference for the government of the Republic of Chad as an essential tool on which policy makers can rely to ensure the security of energy supply of PP in the road transport sector. In the light of the study's findings, the Chadian government should focus on the sharp increase in demand for gasoline and diesel from the road transport sector in the coming years. It is therefore urgent for the government of the Republic of Chad to step up the development of the downstream oil sector, in order to respond effectively to the strong demand for PP in the road transport sector. This could be done by creating a public-private partnership to encourage investment in the oil and gas industry, which is still in its infancy. In addition, develop alternative energy sources and a long-term hybrid vehicle acquisition policy. The Sequential-GM (1,N) and NeuralODE-GM (1,1) models present overall good feasibility, adaptability and predictive accuracy, which could be strongly recommended in terms of predictive models in energy and beyond.

Given the depletion of the oil reserves that feed SRN for the production of PP (TCNTCC, 2020) the high rate of urbanisation, the volatility of crude oil prices on the international market and the government's current policies aimed at making Chad an emerging country by 2030. The desire of the government of the Republic of Chad to reduce consumption and expenditure linked to the consumption of PP. It is time for political decision-makers to take a closer look at the road transport sector, because the demand for PP in this sector is enormous. Despite the fact that the road transport network is still underdeveloped, the demand for PP in this sector between now and 2030 is not negligible. An increase in Chad's crude oil refining capacity would therefore appear to be necessary in order to meet future demand for PP in the road transport sector. Secondly, a policy of planning and developing road infrastructure in urban towns could be envisaged. Encouraging mass transport in urban areas could help to reduce the consumption of PP, in order to make the supply of PP in this transport sector, which is the foundation of social and economic development, sustainable. Lastly, the development of new infrastructure to increase the use of new fuels such as biofuels, liquefied natural gas and liquefied petroleum gas, and the acquisition of new cars using alternative fuels, could help to further reduce the consumption of gasoline and diesel in the transport sector.

REFERENCES

ARSAT. (2022), Autorité de Régulation du Secteur Pétrolier Aval du Tchad. Available from: http://www.arsat.td [Last accessed on 2022 Feb 01].

Augé B. (2011), Les nouveaux enjeux pétroliers de la zone saharienne. Hérodote, 142, 183-205.

Azariah, J.S. (2015), Oil Demand Forecasting in Malaysia in Transportation Sector using Artificial Neural Network (ANN). Malaysia: Universiti Teknologi Petronas Tronoh.

Bahrami, S., Hooshmand, R.A., Parastegari, M. (2014), Short term electric load forecasting by wavelet transform and grey model improved by PSO (particle swarm optimization) algorithm. Energy, 72, 434-442.

BID. (2023), Sortir de la Pauvreté : Développer le Réseau de Transport au Tchad. Available from: https://www.isdb.org/fr/case-studies/sortir-de-la-pauvrete-developper-le-reseau-de-transport-au-tchad [Last accessed on 2023 Jun 05].

Chai, J., Wang, S., Wang, S., Guo, J. (2012), Demand forecast of petroleum product consumption in the Chinese transportation industry. Energies, 5, 577-598.

Chen, H., Tong, Y., Wu, L. (2021), Forecast of energy consumption based on FGM(1, 1) model. Mathematical Problems in Engineering, 2021, e6617200.

Cui, J., Dang, Y.G., Liu, S.F. (2009), Novel grey forecasting model and its modeling mechanism. Control and Decision, 24, 1702-1706.

Deng, J.L. (1982), Control problems of grey systems. Systems and Control Letters, 1, 288-294.

Ding, S., Dang, Y.G., Xu, N., Wei, L., Ye, J. (2017), Multi-variable time-delayed discrete grey model. Control and Decision, 32, 1997-2004.

Ding, S., Hipel, K.W., Dang, Y. (2018), Forecasting China's electricity consumption using a new grey prediction model. Energy, 149, 314-328.

Fani, M., Norouzi, N. (2020), Using social and economic indicators for modeling, sensitivity analysis and forecasting the gasoline demand in the transportation sector: An ANN approach in case study for Tehran metropolis. Iranian Journal of Energy, 23, 71-91.

FMI. (2016), Le secteur Pétrolier du Tchad une Complexité Croissante Pesant Davantage sur Les Dispositifs de Transparence et D'intégrité. Finland: FMI.

Hamzacebi, C., Es, H.A. (2014a), Forecasting the annual electricity consumption of Turkey using an optimized grey model. Energy, 70, 165-171.

Hamzacebi, C., Es, H.A. (2014b), Forecasting the annual electricity consumption of Turkey using an optimized grey model. Energy, 70, 165-171.

Hamzacebi, C., Es, H.A. (2014c), Forecasting the annual electricity consumption of Turkey using an optimized grey model. Energy, 70, 165-171.

Javanmard, M.E., Tang, Y., Wang, Z., Tontiwachwuthikul, P. (2023), Forecast energy demand, CO_2 emissions and energy resource impacts for the transportation sector. Applied Energy, 338, 120830.

Lu, I.J., Lewis, C., Lin, S.J. (2009), The forecast of motor vehicle, energy demand and CO_2 emission from Taiwan's road transportation sector. Energy Policy, 37, 2952-2961.

Massuyeau, B., Dorbeau-Falchier, D. (2005), Gouvernance pétrolière au Tchad: La loi de gestion des revenus pétroliers. Afrique Contemporaine, 216, 139-156.

Özmen, A., Yilmaz, Y., Weber, G.W. (2018), Natural gas consumption forecast with MARS and CMARS models for residential users. Energy Economics, 70, 357-381.

Pukšec, T., Krajačić, G., Lulić, Z., Mathiesen, B.V., Duić, N. (2013), Forecasting long-term energy demand of Croatian transport sector. Energy, 57, 169-176.

Richard, M.P. (2014), Rapport National du Tchad.

Sahraei, M.A., Çodur, M.K. (2022), Prediction of transportation energy demand by novel hybrid meta-heuristic ANN. Energy, 249, 123735.

Sapnken, E.F., Tamba, J.G., Djanna Koffi, F.L. (2017), The variability of gasoline demand in Cameroon. Energy Sources, Part B: Economics, Planning, and Policy, 12, 772-778.

Sapnken, F.E. (2023), A new hybrid multivariate grey model based on genetic algorithms optimization and its application in forecasting oil products demand. Grey Systems: Theory and Application, 13, 406-420.

Sapnken, F.E., Acyl, A.K., Boukar, M., Nyobe, S.L.B., Tamba, J.G. (2023a), A technique for improving petroleum products forecasts using grey convolution models and genetic algorithms. MethodsX, 10, 102097.

Sapnken, F.E., Ahmat, K.A., Boukar, M., Biobiongono Nyobe, S.L., Tamba, J.G. (2022a), Forecasting petroleum products consumption in Cameroon's household sector using a sequential GMC(1,n) model optimized by genetic algorithms. Heliyon, 8, e12138.

Sapnken, F.E., Ahmat, K.A., Boukar, M., Biobiongono Nyobe, S.L., Tamba, J.G. (2022b), Forecasting petroleum products consumption in Cameroon's household sector using a sequential GMC(1,n) model optimized by genetic algorithms. Heliyon, 8, e12138.

Sapnken, F.E., Ahmat, K.A., Boukar, M., Nyobe, S.L.B., Tamba, J.G. (2023b), Learning latent dynamics with a grey neural ODE prediction model and its application. Grey Systems: Theory and Application, 13, 488-516.

Sapnken, F.E., Hamed, M.M., Soldo, B., Gaston Tamba, J. (2023c), Modeling energy-efficient building loads using machine-learning algorithms for the design phase. Energy and Buildings, 283, 112807.

Sapnken, F.E., Tamba, J.G. (2022), Petroleum products consumption forecasting based on a new structural auto-adaptive intelligent grey prediction model. Expert Systems with Applications, 203, 117579.

Sapnken, F.E., Tamba, J.G., Ndjakomo, S.E., Koffi, F.D. (2020), Oil products consumption and economic growth in Cameroon households: An assessment using ARDL cointegration and granger causality analysis. International Journal of Energy Economics and Policy, 10, 510-523.

Shen, Q.Q., Cao, Y., Yao, L.Q., Zhu, Z.K. (2021), An optimized discrete grey multi-variable convolution model and its applications. Computational and Applied Mathematics, 40, 58.

SHT. (2023), Vision. Société des Hydrocarbures du Tchad. Available from: https://sht-td.com/vision [Last accessed on 2023 May 17].

Sonmez, M., Akgüngör, A.P., Bektaş, S. (2017), Estimating transportation energy demand in Turkey using the artificial bee colony algorithm. Energy, 122, 301-310.

Tamba, J.G., Essiane, N., Sapnken, E.F., Koffi, F.D., Nsouand, J.L., Soldo, B., Njomo, D. (2018), Forecasting natural gas: A literature survey. International Journal of Energy Economics and Policy, 8, 216.

Tamba, J.G., Nsouandélé, J.L., Sapnken, E.F., Djanna Koffi, F.L. (2017), The variability of diesel demand in Cameroon. Energy Sources, Part B: Economics, Planning, and Policy 12, 868-875.

TCNTCC. (2020), Troisième Communication Nationale du Tchad sur les Changements Climatiques, République du Tchad.

Teng, G., Xiao, J., He, Y., Zheng, T., He, C. (2017), Use of group method of data handling for transport energy demand modeling. Energy Science and Engineering, 5, 302-317.

Tien, T.L. (2012), A research on the grey prediction model GM (1, n). Applied Mathematics and Computation, 218, 4903-4916.

Tseng, F.M., Yu, H.C., Tzeng, G.H. (2001), Applied hybrid grey model to forecast seasonal time series. Technological Forecasting and Social Change, 67, 291-302.

Wang, C., Cao, Y. (2021), Forecasting Chinese economic growth, energy consumption, and urbanization using two novel grey multivariable forecasting models. Journal of Cleaner Production 299, 126863.

Zhang, M., Mu, H., Li, G., Ning, Y. (2009), Forecasting the transport energy demand based on PLSR method in China. Energy, 34, 1396-1400.