Using neural network modelling for estimation and forecasting of transport sector energy demand in developing countries

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Abstract

In developing countries, national-level institutions are often limited by key transportation energy efficiency indicators. A transportation model based on 40 artificial neural networks was developed to fill this gap. Data on energy efficiency indicators for 28 European countries have been collected to train a model for predicting these indicators using socio-economic variables. A bottom-up approach is then used to compare the predicted data to the total energy consumption. Morocco is used as a case study because of the absence of its energy efficiency indicators. The model's outstanding performance was proved after calculating energy demand at a highly disaggregated level. The model was used to forecast energy consumption up to 2050, considering a variety of alternative hypotheses. Four long-term energy demand scenarios were evaluated: frozen efficiency, implementation of EU legislation, cars electrification, and modal shift. The redistribution of passenger kilometres and tonne-kilometres as a way of rising average occupancy and average load revealed a significantly greater potential for energy savings. Switching from diesel to biofuel for buses and light cars was also examined as a solution to minimize GHG emissions. The developed model supplies decision-making institutions with the necessary tools for identifying critical issues, implementing policies, and redistributing infrastructure.

Keywords: ANN, Transport sector, Energy efficiency indicators, Energy demand, Bottom-up approach

Nomenclature

AL	Average Load
ANN	Artificial Neural Network
AO	Average Occupency
AVKM	Average vehicle kilometres travelled
BaU	Business as Usual
CV	Quantity of heat produced during the combustion of fuel
E	Energy
EF	Emission Factor
EU	Europeen Union
FE	Fuel Economy
GDP	Gross domestic product
GFEI	Global Fuel Economic Initiative
GHG	Greenhouse Gas
GWP	Global Warming Potential
HCP	Haut-Commissariat au plan
HFCE	Household final consumption expenditure
IEA	International Energy Agency
NSV	Stock of new vehicles entering the system
PD	Population Density
PI	Price Index
PKM	Passengers Kilometres
PPD	Pump Price Diesel
PPG	Pump Price Gasoil
PPP	Purchasing Power Parity

RMSE	Root Mean Square Error
SV	Stock of vehicles
TKM	Tonnes kilometres
VKM	Vehicle kilometres
XSV	Stock of vehicles exiting the system
HSBC	Hong Kong & Shanghai Banking Corporation

1. Introduction

Energy efficiency indicators are widely regarded as a critical instrument for assisting policymakers in focusing their efforts, designing successful policies, and monitoring progress toward policy objectives. As a result, worldwide efforts are being made in significant numbers to develop indicators and to draw conclusions from national and international trends and comparative studies. However, a lack of data constrains the role of energy efficiency indicators in policymaking in developing countries, and much effort is necessary to facilitate indicator development and application [1].

The resources required to develop meaningful energy efficiency indicators will be costly and time-consuming. The first indication of resource requirements comes from the ODYSSEE experience, which requires an annual budget of one million euros to develop and manage energy efficiency indicators of 28 countries. The ODYSSEE database contains more than 180 indicators that have the purpose of monitoring and evaluating the annual energy efficiency trends and energy-related CO_2 emissions in all the sectors and in priority areas to address EU policies. This database encompasses several indicators, calculated at a macro-economic, sectoral, sub-sector and end-use level. Furthermore, based on experience with the new EU countries that have joined the project, it appears that bringing such countries up to speed generally takes roughly four years [2][3].

When data collection is done appropriately (more diverse), it can focus on energy efficiency issues. In this regard, care must be taken to define and select indicators to reflect the data generated across countries. However, the availability of data on energy efficiency indicators can be impeded by its underlying divers. In general, more disaggregated data provide a better understanding of such drivers, although data at a higher aggregation level (sector as a whole: industry, households, transportation) are the most easily obtainable. This issue is worsened in less developed countries, where data availability and infrastructure are much more limited [1].

This paper enables countries (particularly emerging economies) that lack transportation energy efficiency indicators to generate their own. An Artificial Neural Network (ANN) algorithm is to provide practical information on the generation of data for the calculation, interpretation, and evaluation of these indicators [4][5]. This branch of artificial intelligence uses mathematical and statistical techniques to enable computers to "learn" from existing data (or examples) to develop outputs for any set of input parameters. This self-learning process involves establishing a correlation between the complex system's input and output variables. Data on the energy efficiency indicators of 28 European countries are used for that purpose.

The choice of these European countries for learning the model was made for two main reasons. First, these countries have the necessary output data for learning gathered by ODYSEE-Mure Database. The second reason is that the economic power in these countries is very diverse, which help o better narrow in on energy efficiency issues. Europe's countries are divided into "Advanced Europe" and "Emerging and Developing Europe," sometimes known as central and eastern Europe. ~~Repatriation of Poland, Romania, Ukraine, Hungary, Serbia, and Croatia.~~ Apart from economic development, the Eastern European periphery continues to be a representation of underdevelopment and inequality in the EU. For example, Romania is ranked 46th in the world in terms of GDP, Ukraine is 57th, Bulgaria is 76th, Croatia is 77th, Belarus is 78th, and Serbia is 86th (Morocco is 59th) [6].

EU member states have diverse infrastructural requirements and energy efficiency indicators in the transportation sector. While some EU countries' primary objective is to improve and preserve existing infrastructure, others must create or extend their transportation networks. Transport infrastructure availability and quality are notably low in the Eastern part of the EU. Given regional disparities and differences in transportation patterns, one feasible indicator for comparing the situation across EU countries is satisfaction with the quality of transportation infrastructure. The World Economic Forum produces it for its Global Competitiveness Report. Satisfaction with transportation infrastructure is lowest in Central and Eastern European countries, specifically Bulgaria, Poland, Romania, Slovakia, Slovenia, Greece, and Malta [7].

On the other hand, Germany, Spain, Finland, France, and the Netherlands rank highest. Bulgaria has the lowest perceived quality of transport infrastructure of all EU member states. Due to the budgetary and structural constraints in Bulgria, transportation infrastructure modernization has been slow. Ireland invests less in transportation infrastructure as a percentage of GDP than the rest of the EU and far less than the level estimated to maintain the current system. Poland lacks an integrated structure of highways and expressways connecting major cities and industrial districts. Additionally, the railway network's deteriorating condition reduces its competitiveness and impairs the quality of rail transport services [8].

The development of a learning model taking into account all this diversity in the transport sector would undoubtedly be robust for predicting outputs according to new socio-economic parameters of a given country. Therefore, the present paper identified two critical areas for developing countries where energy efficiency indicators are particularly needed:

- Data and indicator generation for developing economies, as the energy efficiency indicators, could not be provided due to a lack of consistent data (now only available for developed countries).
- Developing a strategy for advancing policy development by conceiving future scenarios that could serve as possible solutions for achieving long-term energy demand.

To fill these gaps, data on the energy efficiency indicators of 28 European countries (Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malte, Netherlands, Austria, Poland, Romania, Slovenia, Finland, Sweden, Norway, and the UK) were collected during 30 years [2][3]. Indeed, for each country, mode of transport, and type of vehicle fuel, average occupancy (AO) and average vehicle kilometre (AVKM), Average Load (AL), Fuel Economy (FE), and Stock Vehicles (SV) were utilized for training the machine on the country's socio-economic variables. In addition, the GDP, population (P), Pump Price Gasoline (PPG), Pump Price Diesel (PPD), the Price Index (PI), Purchasing Power Parity (PPP), Household Final Consumption Expenditure (HFCE), and Population Density (PD) [9] were chosen as explanatory socio-economic parameters. Finally, the output data are checked against the overall energy consumption data in the country's national statistics using a bottom-up approach (Methodology section). Once trained and validated, the model may generate a country's missing energy efficiency indicators using its eight socio-economic parameters. The model could then be used to forecast and model the future energy transportation system, treating the prediction inputs as additional unknown data.

The first objective of this study is to develop a general model able to "learn" from energy efficiency indicators of 28 European countries in a time period of 30 years. The model is used to generate higher-disaggregated energy efficiency indicators to describe the efficiency of the transportation sector in developing countries, based on historical data for GDP, population, Pump Price Gasoline, Pump Price Diesel, the Price Index, Purchasing Power Parity, Household Final Consumption Expenditure, and Population Density

The second objective is to forecast energy demand for multiple scenarios:

- Frozen efficiency: business is expected to operate as usual (BaU).
- A gradual introduction of an electric car in the transportation system using a sigmoid function.
- Redistribution of both PKM and TKM through increasing occupancy and load of specific vehicle types (modal shift)

Once trained and validated, the model should demonstrate its accuracy to generate energy efficiency indicators only from socioeconomic data (inputs) for a given country. The model is applied to the case study of Morocco, which is an ideal illustration of a complex transportation system with little or no available energy efficiency indicators in the transportation sector [10]. By considering that more than 85 % of Moroccan transport equipment is imported from Europe, the impact of FE reduction according to EU legislation is assessed primarily for that case study [11]. Furthermore, Morocco has strengthened its international energy relations by establishing bilateral agreements with France, Germany, the European Union, and its Mediterranean neighbours. The government signed an Association Agreement with the European Union (EU) in 2000 and benefits from EU funds and assistance under the European

Neighbourhood Policy (ENP) and the associated European Neighbourhood Instrument (ENI) [10]. Therefore, the analysis in the context of EU legislation could be forsaken for another case study.

The model could forecast future energy consumption up to 2050, depending on the socio-economic data's quality provided by national and international economic experts. In addition, the model's efficiency indicators enable a deeper understanding of the factors affecting overall energy consumption and transportation emissions for decision-making institutions for an efficient transport system by implementing policies effectively.

2. Literature review

At the national level of energy balances, the transport sector is divided into passenger and freight transport sectors. Both sectors' data are segmented into four subsectors: road, rail, air, and water, defined by various vehicle types. The amount of financial and technical resources in developed countries allows the collection of detailed road transport indicators by vehicle type [1]. Each country's road transport structure determines the extent to which data are disaggregated [12]. Additionally, it is contingent upon the availability of data for various subsectors [13]. Indeed, one can create highly disaggregated indicators or stay at a too aggregated level for energy efficiency analysis [14]. The most aggregated measures are the transportation sector's share of Total Final Consumption, the consumption of a specific subsector, such as rail, road, water, or air, or freight or passengers. While these measures allow for extremely rough comparisons across countries across time (and are frequently inaccurate), they cannot be used as energy efficiency indicators [15]. Instead, energy and activity data more disaggregated, such as AO and AVKM, are used to create relevant energy efficiency indicators [16]. These indicators are critical for informing policy and investment decisions because they allow for tracking performance over time and a better understanding of the underlying causes of energy demand [17].

Models of the transportation sector are frequently constructed from the bottom-up approach using statistical data or engineering measures [18]. They may simply estimate vehicle stock flows and associated energy consumption statistically, or they may take a more comprehensive engineering approach, including comprehensive technical specifications for vehicles [12]. The bottom-up models are constructed using data such as fuel consumption by mode, PKM and TKM per mode, and vehicle type as model inputs [19] which offers a more accessible possibility to decouple the energy demand to the evolution of the GDP [12]. These data can be collected through national investigations or government procedures, such as those obtained through automobile registration databases. The input data's reliability and the assumptions' accuracy significantly impact the output's consistency [20].

According to the literature, several recent studies demonstrate that using ANNs to model a complex energy system is one of the best Energy and CO_2 forecast tools [21]. For example, Urosevic et al. demonstrated that using historical energy data for the European Union from 1990, the learning system can predict 2050 behaviour [22]. However, disaggregating the entire energy system could yield better benefits. According to Wang et al., ANNs possess a self-learning ability and look for optimal solutions to predict outputs. Additionally, they can completely approximate any arbitrarily complex non-linear relationship and learn and adapt to unknown or unpredictable systems [23].

One of the main advantages of ANN models is that they are not affected by eventual collinearities among inputs [12]. Collinearity occurs when one input variable in a multiple regression model can be predicted linearly from the others. As a result, results may be biased or inaccurate. Fortunately, ANN models are naturally immune to collinearity between inputs. However, other methods, such as Logistic or Linear Regression, are not immune to this issue, which should be addressed before training the model. Collinearity between inputs is often eliminated in ANN models because they tend to be overparameterized. The additional learned weights generate redundancies [24], [25].

This exact redundancy makes the individual weights worthless. The inputs at each network level are linear combinations of the previous level's inputs. The final output is a function of many combinations of sigmoidal functions involving high order interactions with the initial inputs [26].

In other words, ANN models can directly capture non-linear interactions between inputs and outputs variables. They eliminate the need to prove that input variables are uncorrelated using statistical tests to construct the models. Additionally, ANN models integrate multiple inputs and model adjustment in response to ~~the addition of~~ additional data. Furthermore, when the sample size and number of variables increase, the performance of ANN models improve [27].

Establishing the modelling framework, specifying model assumptions and input data, running the model, validating its outputs against the data, and interpreting the results are all critical in the modelling process [28]. It would be essential to generate many hypotheses with missing data to estimate the energy consumption and CO_2 emissions reductions associated with the various modalities. The output data is generally checked against national total sector energy consumption figures [28][1]. Indeed, studies employing bottom-up methodologies have succeeded in developing more realistic and consistent prediction models, depending on the size and quality of the incoming data. Peng et al., for example, developed a bottom-up model to forecast future energy demand and greenhouse gas (GHG) emissions from Chinese road transport at the provincial level, taking into account local economic development and population [29]. Tang et al. also employed a bottom-up methodology based on assessing the factors influencing energy consumption to forecast the future development trend of passenger transport, taking GDP, population, and transportation infrastructure into account[30]. The highly disaggregated data inputs enabled the development of a technology roadmap to 2050 and the identification of political consequences for passenger transport. Verdezoto et al. assess the energy matrix's behaviour in perspective of energy predictions and efficiency policy scenarios, using a bottom-up approach to forecast energy demand up to 2030 while considering Ecuador's local policy and infrastructure development history[31].

Additionally, as Sonmez et al. [16] demonstrated, efforts have been undertaken to establish a link between energy indicators and GDP to forecast transportation energy demand. However, given the model's reliance on a single indicator, it may prove to be constrained. Because the quality of the model findings is heavily dependent on the quality of the input data and the accuracy of the assumptions, the absence of or low quality of input data could weaken the model's accuracy for the estimates and limit the model's accuracy [32]. According to Sahraei et al., transport energy demand is predicted using GDP, population, VKM, TKM, PKM, and oil prices [20]. While these factors influence energy demand, additional variables can be included for more accurate modelling. Indeed, for each country, mode of transport, and type of vehicle fuel, AVKM, AO, AL, FE, and SV were utilized for training the machine on the country's socio-economic variables.

However, studies have utilized various energy efficiency indicators in developing countries, as illustrated in Table 1, where the gap is noted to calculate energy demand and energy efficiency improvements, where AVKM, AO, AL, FE, PKM, TKM and SV data are used.

For Algeria [33], Morocco [34], Iran [35], Ethiopia [36], as for the Africa continent [37], the studies used only P and GDP to describe historical energy demand for the transportation sector. The long term energy demand planning has been left to highly aggregated trend analyses. These types of models have the highest probability of producing outrageous predictions.

Efforts have been made to integrate some energy efficiency indicators for the transportation sector. Still, they remain deficient in developing a better understanding of the drivers and prospects for energy efficiency, in better informing the policy process and assisting decision-makers in developing policies that are most compatible with domestic and international policy objectives [38][39][40][41][42][43][44].

Table 1 Transport energy demand studies related to developing countries

Country	The objective of the study	Energy efficiency indicators	
		Used	Lacking
Philippines [38]	Forecasting total energy demand	PKM, TKM	AVKM, AO, AL, FE, SV
Pakistan [39]	Forecasting natural gas demand	-	AVKM, AO, AL, FE, SV, PKM, TKM
Algeria [33]	Forecasting total energy demand	-	AVKM, AO, AL, FE, SV, PKM, TKM
Morocco [34]	Forecasting total energy demand	-	AVKM, AO, AL, FE, SV, Pkm, Tkm

Iran [35]	Forecasting total energy demand	-	AVKM, AO, AL, FE, SV, PKM, TKM
Iran [40]	Forecasting Gasoline demand	SV, AO, AVKM, PKM (indicators for light vehicles only)	AL, FE, TKM
Thailand [41]	Forecasting transport energy demand	SV	AVKM, AO, AL, FE, PKM, TKM
Nigeria [42]	Forecasting GHG emissions	SV, AVKM	AO, AL, FE, PKM, TKM
Africa [37]	Forecasting total energy demand	-	AVKM, AO, AL, FE, SV, PKM, TKM
Jordan [43]	Forecasting transport energy demand	SV, AO	AVKM, AL, FE, TKM, PKM
Brazil [44]	Forecasting total energy demand	SV	AVKM, AO, AL, FE, PKM, TKM
Ethiopia [36]	Forecasting total energy demand	-	AVKM, AO, AL, FE, SV, PKM, TKM

With minimal data, few indicators, and few indicators, it is evident that establishing a meaningful assessment of a situation is difficult, if not impossible. Thus, this information gap impedes the optimization of measures and policies and predicts future energy demand. For instance, the evaluation of energy savings by redistributing PKM and TKM could not be assessed in studies involving developing countries due to a lack of average occupancy and average load data.

As documented in the literature, it is possible to conclude that data availability for indicator formulation and use in those nations is quite limited. However, most countries lack data on energy consumption, particularly at the sub-sectoral level and activities. The proposed model in this study could fulfil this particular gap.

Thus, the primary objective was to establish a correlation between a country's socioeconomic characteristics and energy efficiency indicators. To that end, energy efficiency indices for 28 European countries were collected (output) to train the model using socioeconomic data from each country (inputs). Once trained and validated, the model may be used to create missing energy efficiency indicators for any country based on its socioeconomic variables (inputs).

3. Methodology

There are four main steps in developing an ANN model:

- The first step is to select and prepare a training data set. This data is used to provide input for the ANN model to learn how to generate new outputs from new inputs.
- The second step is to select an architecture to run on the training data set.
- The third step is model training. This is an iterative process. First, inputs are run through the model, and the outputs are compared with what it should have produced. The “weights” and bias can then be adjusted to increase the accuracy of the result. The variables are then run again until the algorithm produces the correct outputs most of the time.
- The fourth and last step is using the model to generate outputs according to new inputs. In this case study, the socioeconomic variables of Morocco are used as inputs.

Regarding the input variables, eight socioeconomic variables are chosen to generate the outputs since many studies identified the strong links and interactions between energy and socio-economic variables [45][46][47]. The most influencing variables are GDP [48], population [49], Pump Price Gasoline [50], Pump Price Diesel [51], the Price Index [52], Purchasing Power Parity [53], Household Final Consumption Expenditure [54], and Population Density [55].

The socioeconomic variables of 28 European countries are collected to be the model's input variables. The output variables for each mode of transport and fuel type of vehicle are AO, AL, FE, and SV of each European country.

The ANN model is trained using statistics from 28 European countries from 1990 to 2019 to demonstrate the approach's effectiveness. The output data are validated by comparing them to the total energy consumption data using the bottom-up approach. As noted previously in the Introduction section, once trained, the model may be used to generate the outputs (energy efficiency indicators) for any value of the inputs (socio-economic variables). When a country or region lacks energy indicators, the output data are compared to the overall energy consumption data available in the country's national statistics [28][1]. Finally, once the model is trained and validated, it can forecast future energy indicators. In fact, the model will respond to the forecasted input data as "new" ones. However, since the model does not forecast the socioeconomic parameters (inputs), these parameters need to be calculated apart. Consistency of the results in the future is mainly sensitive to the accuracy of the socioeconomic parameters forecast (model input parameters).

Additional scenarios can be developed and compared to the BaU scenario. The model and its concept are depicted in Figure 1. Section 3.2 discusses the ANN model's fundamental methodology in the contexts of its subsectors.

The indicators presented in this study were chosen to identify the essential components required for assessing the transportation sector's energy demand. This methodology connects travel behaviour, the structure and components of the transportation system, fuel efficiency and emission parameters to energy consumption and emissions using the bottom-up approach.

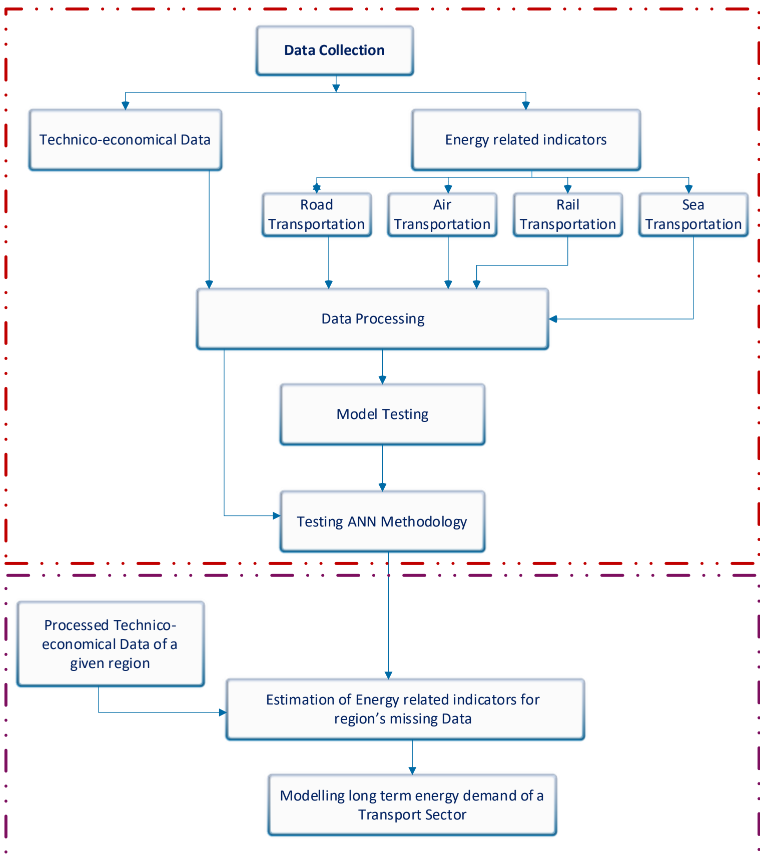

Figure 1 Overview of the ANN model

3.1. Selected indicators

According to the International Energy Agency (IEA) [28] and ODYSSEE [56], the following indicators offer a better comprehension of the elements affecting total transportation energy consumption and emissions. In addition, it reveals additional pieces of information aimed at improving the efficiency or pollution level of systems.

3.1.1. Total road vehicle-kilometres travelled VKM

This indicator illustrates ~~that~~ the average annual mileage travelled by a particular vehicle type. It is frequently used as the primary activity data for bottom-up analyses of the energy consumption and emissions associated with road transportation. Disaggregated AVKM data by vehicle type and fuel type can shed light on a country's vehicle activity. In an idealistic situation, complete AVKM estimates could be derived from odometer readings collected during routine vehicle inspections and registrations. However, this is not practised in a large number of countries. In the absence of robust data, equation (1) provides a simple technique for estimating total VKM travelled for year z for a vehicle type i operating on a fuel type j via a mode of transport m [17]:

$$VKM_{i,j}^{m,z} = SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} \quad (1)$$

To obtain a credible estimate of the total VKM, predicting the SV and the AVKM are required.

3.1.2. Total passenger-kilometres by transport mode PKM

A PKM is a unit of transportation activity that refers to the transportation of a single passenger over a one-kilometre distance. Monitoring this indicator enables an assessment of the passenger transport sector's overall growth. It would be highly beneficial if PKM data could be disaggregated by mode, vehicle type, and fuel type since this would aid in identifying policy priorities and future initiatives. In developed countries (e.g., the EU Member States), aggregated PKM estimates are derived from sample surveys based primarily on trip diaries. In the absence of such surveys, equation (2) provides a simplified way for estimating PKM values for a specific mode of transport using a vehicle type i and a fuel type j [17]:

$$PKM_{i,j}^{m,z} = SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} * AO_{i,j}^{m,z} \quad (2)$$

The term "average vehicle occupancy" refers to the number of people carried on an average trip by a particular type of passenger vehicle. Vehicles with a higher occupancy rate are more efficient in transporting passengers than lower ones. Additionally, it gives data to aid in developing travel demand management initiatives and public transportation systems.

The total PKM for a particular mode of transport m in the year z is equal to the sum of all PKM values for that transport mode (equation (3)) [17]:

$$PKM^{m,z} = \sum_i \sum_j SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} * AO_{i,j}^{m,z} \quad (3)$$

After estimating the SV and AVKM, it is necessary to predict the average occupancy of a passenger vehicle for vehicle type i using a fuel type j in a transport mode m.

3.1.3. Total Tonnes-kilometres by transport mode TKM

This indicator is a unit of measurement for the distance travelled over a kilometre by one ton of freight. By combining the distance travelled and the quantity of goods transported, this indicator depicts the level of freight activity. Monitoring such an indicator can shed light on the freight's growth rate. Comparing mode-specific data also highlights the relative importance of each mode in carrying out freight activities, informing policymaking and intervention decisions. In the absence of complete data, the average TKM is calculated using the equation (4) [17]:

$$ATKM_{i,j}^{m,z} = SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} * AL_{i,j}^{m,z} \quad (4)$$

Freight vehicle load factors are a proxy for freight transport efficiency, as they indicate how much of the freight vehicle fleet's overall capacity is being utilized. Therefore, the increased load capacity can help reduce freight VKM by avoiding ~~the need for~~ additional vehicles.

The total TKM for a particular mode of transport m in the year z is equal to the sum of all PKM values for that transport mode (equation (5)) [17]:

$$TKM^{m,z} = \sum_i \sum_j SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} * AL_{i,j}^{m,z} \quad (5)$$

Developing comparable metrics for alternative modes of transport (for example, water-based) enables a more holistic view of how freight activity and growth are segmented across the various modes.

3.1.4. Average road vehicle fuel economy

The average vehicle fuel economy indicator indicates how much fuel a vehicle consumes per unit of distance travelled. This indicator indicates the average efficiency of a fleet's vehicles by displaying the amount of fuel or energy consumed per vehicle kilometres travelled. In addition, it provides necessary data for interventions aimed at increasing the energy efficiency of future vehicle fleets, such as fuel economy standards for new vehicles, fuel economy labelling, and incorporating fuel economy considerations into vehicle taxation and incentive programs. This metric is expressed in terms of litres of fuel type consumed per 100 kilometres.

The equation (6) below illustrates how the Global Fuel Economic Initiative (GFEI) calculates average FE for the year z+1, principally to determine averages for new entries to the vehicle fleet in terms of fuel economy values for the year z [17].

$$FE_{i,j}^{m,z+1} = FE_{i,j}^{m,z} * \left(1 + \frac{NSV_{i,j}^{m,z+1} - XSV_{i,j}^{m,z+1}}{SV_{i,j}^{m,z}}\right) \tag{6}$$

Where:

NSV: is the stock of new vehicles entering the system

XSV: is the stock of vehicles exiting the system

3.1.5. Total energy consumption by transport mode

This indicator measures the total amount of energy utilized by the transportation sector during a specific period. It is intended to keep track of the transportation sector's total energy use. Bottom-up estimation is a technique for estimating disaggregate values from smaller components. The following equation illustrates how to calculate such energy demand for a vehicle type i operating on a fuel type j in a mode of transport m in the year z [17]:

$$E_{i,j}^{m,z} = SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} * FE_{i,j}^{m,z} * CV_j \tag{7}$$

Where:

CV: is the quantity of heat produced during the combustion of fuel.

The total energy demand for a particular mode of transport m in a given year z is equal to the sum of all energy demand values for that transport mode (equation (8)) [17]:

$$E^{m,z} = \sum_i \sum_j SV_{i,j}^{m,z} * AVKM_{i,j}^{m,z} * FE_{i,j}^{m,z} * CV_j \tag{8}$$

3.1.6. Total GHG emissions by transport mode

This indicator illustrates the transportation sector's contribution to greenhouse gas emissions. Typically, official estimates include the Kyoto Protocol gases that affect the transportation sector: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (NOx). CO_2 is the primary source of pollution in the transportation sector, as it is produced directly during the complete combustion of standard transportation fuels. Numerous countries also account for indirect greenhouse gas emissions and precursor molecules such as carbon monoxide, non-methane volatile organic compounds, sulphur dioxide, particulate matter, and nitrogen oxides.

Total GHG emissions from a particular mode of transport m in the year z are equal to the sum of all GHG emissions from that transport mode (equation (9)) [17]:

$$GHG^{m,z} = \sum_i \sum_j E_{i,j}^{m,z} * \mathrm{EF}_j * FE_{i,j}^{m,z} * GWP_j \tag{9}$$

Where:

E: is the transport energy consumption

EF: is the Emission Factor for the GHG emissions corresponding to fuel type j

GWP: is the Global Warming Potential

For an accurate level of disaggregation, transportation energy indicators are collected for each type of vehicle and each type of fuel, as summarized in Figure 2.

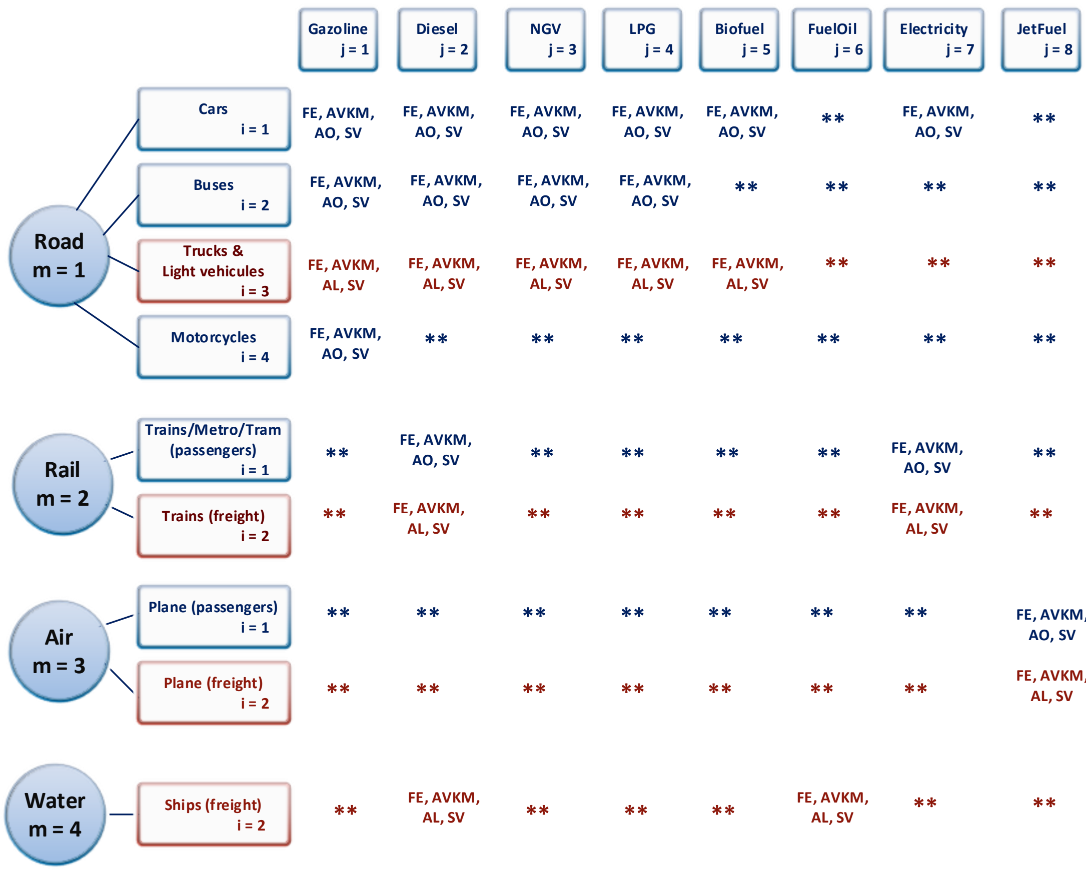

Figure 2 Transportation efficiency indicators of vehicles and fuel types

3.2. ANN Modeling

ANNs are a substitute for mathematical modelling and are included in nonparametric and non-linear statistical models capable of solving identification and prediction in complex energy systems [12]. A neural network is associated with several artificial neurons coupled by weights whose values impact the structure's behaviour. The network learning algorithm is defined by the principles that regulate the adjustment of connections between layers (Supervised and Non-supervised rules).

Unlike the non-supervised rules, the supervised learning rule is employed because the external environment provides desirable outputs for each incoming input and functions as an instructor. The network employs an approach that ensures that the computed output converges to the target value across successive iterations. The Perceptron (MLP) algorithm is a popular supervised learning approach that uses continuous data. A Perceptron contains at least three layers: an input layer that receives input variables, an output layer that generates the network's output, and a variable number of hidden layers that perform internal calculations. Generally, only one hidden layer is required [12]. The Levenberg-Marquardt algorithm is used because it is an optimization approach for minimizing sums of square functions [57].

Figure 3 illustrates the basic operations used in this model. For m the number of variables (inputs) and n the number of neurons in the network, ∀ i ϵ [1,m], ∀ j ϵ [1,n], the general requirement for learning is an algorithm that adjusts the network weights W_{ij} (associated with the input layer) and W'_j (associated with the output layer) to minimize the difference between the actual outputs act and the desired (or predicted) outputs.

Numerous ANN structures are currently in use, which can be classified according to their structure and characteristics. In any artificial neuron, the first step is to add the various inputs X_i multiplied by their associated connection weights W_{ij}. Then, the summation function is fed the products [58]:

$$S_j = \sum_{i=1}^{m} W_{ij} * X_i \tag{10}$$

Whichever way the value S_j is computed, it is then used to calculate the activation function, which determines whether the input X_i is taken into account, and the neuron is activated. The sigmoid function is used as an activation function for neurons in the hidden layer [58]:

$$h_j = f(S_j) = {}^{1}/_{1+e^{-bS_j}} \tag{11}$$

Likewise, the summation of the various inputs h_j multiplied by their respective connection weights W'_j. Then, the products are fed into the summation function:

Similarly, the sum of the various inputs h_j multiplied by the weights of their respective connections W'_j. Then, the summation function is fed the products [58]:

$$S'_j = \sum_{j=1}^{n} W'_j * h_j \tag{12}$$

The sigmoid function is used as the activation function for the output layer [58]:

$$pred = g(S'_j) = a * S'_j + b \tag{13}$$

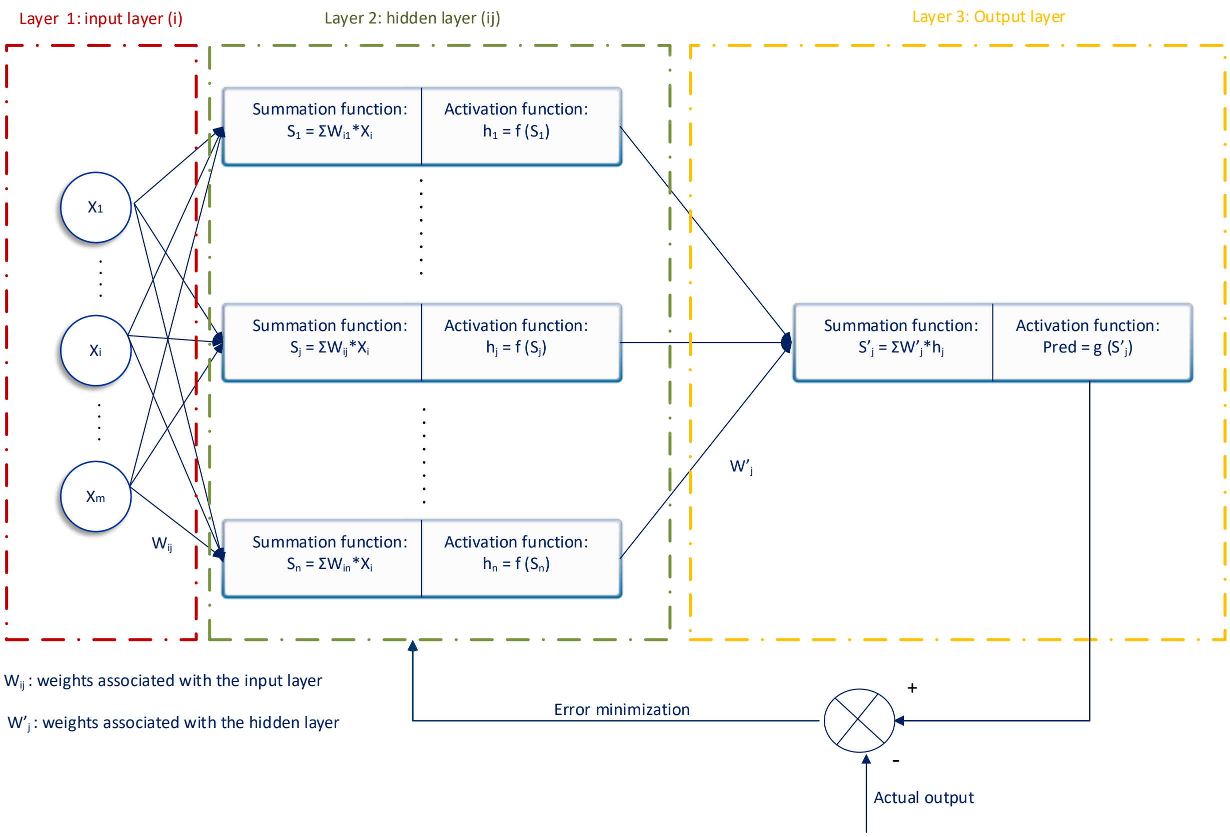

Figure 3 Model's operations

To make the model learn from the data, training and validation sets are required to optimize the architecture of the networks. A test set could be used to see how well the model is performing on totally unknown data. The used database in this study is subdivided into three sets: 70% for training (or learning) the model, 15% as the validation set and 15% for testing the model. These data sets are selected randomly. The Neural Networks toolbox of the Matlab software was used to train, validate and test the model.

To estimate the performance of a neural model, the most frequently used performance index is the Root Mean Square Error (RMSE)[59][60][61]. It consists of looking for a parameterized function $pred(X_k, w_{ij}, w'_j)$ performed using a neural network, for which the error function $E_{RMSE}(w_{ij}, w'_j)$ is minimum:

$$E_{RMSE}(w_{ij}, w'_j) = \frac{1}{N} \sum_{k=1}^{8} [pred(X_k, w_{ij}, w'_j) - act]^2 \tag{14}$$

Regarding ANNs architecture networks, the number of neurons in the hidden layer is a critical hyperparameter. Our strategy is to vary the number of neurons in the hidden layer and then choose the optimal network with minimal possible RMSE.

To improve the performance of ANN and allow better convergence of the network, it is preferable to normalize the input and output data of the model in the interval [0,1]. The function used for normalization is expressed by:

$$\forall\ i \in [1,m],\ \forall\ j \in [1,N] \begin{cases} y_i^j = \dfrac{x_i^j - \min\limits_{1\le j\le N}\left(x_i^j\right)}{\max\limits_{1\le j\le N}\left(x_i^j\right) - \min\limits_{1\le j\le N}\left(x_i^j\right)} \\ X_i = \{x_i^1, x_i^2, x_i^3, \dots, x_i^N\} \end{cases} \tag{15}$$

Eight inputs are set as variables: GDP, population, Pump Price Gasoline, Pump Price Diesel, the Price Index, Purchasing Power Parity, Household Final Consumption Expenditure, and Population Density. Each input variable contains 840 data (N = number of countries * number of years = 28 * 30).

For each type of vehicle (Figure 2), four different networks corresponding to AVKM, SV, FE and (or AL) defined by their number of neurons in the hidden layer were used in this model. The number of outputs of each network depends on the number of fuels used by each type of vehicle (Equation 16). For m $\in$ [1,4], $\forall$ i $\in$ [1,4], $\forall$ j $\in$ [1,8], $pred_j^m$= { $AVKM_{i,j}^m, SV_{i,j}^m, FE_{i,j}^m, AO_{i,j}^m, AL_{i,j}^m$} (16)

For example, to predict the four energy indicators for cars, the four different networks with various node numbers have six outputs corresponding to the number of fuels used by this type of vehicle (gasoline, diesel, LPG, NGV, biofuel, and electricity). By analogy, the four networks of freight trains have only two outputs. Following this logic, this model employs 40 distinct networks consecutively to maximize learning. Eighty thousand six hundred forty data were used to train the model.

4. Results and Discussion

4.1. Model validation

To optimize the architecture of each network, the number of neurons N in the hidden layer was evaluated. A loop test was used to vary N between 1 and 200 to determine the optimal N for each network. The RMSE for each N

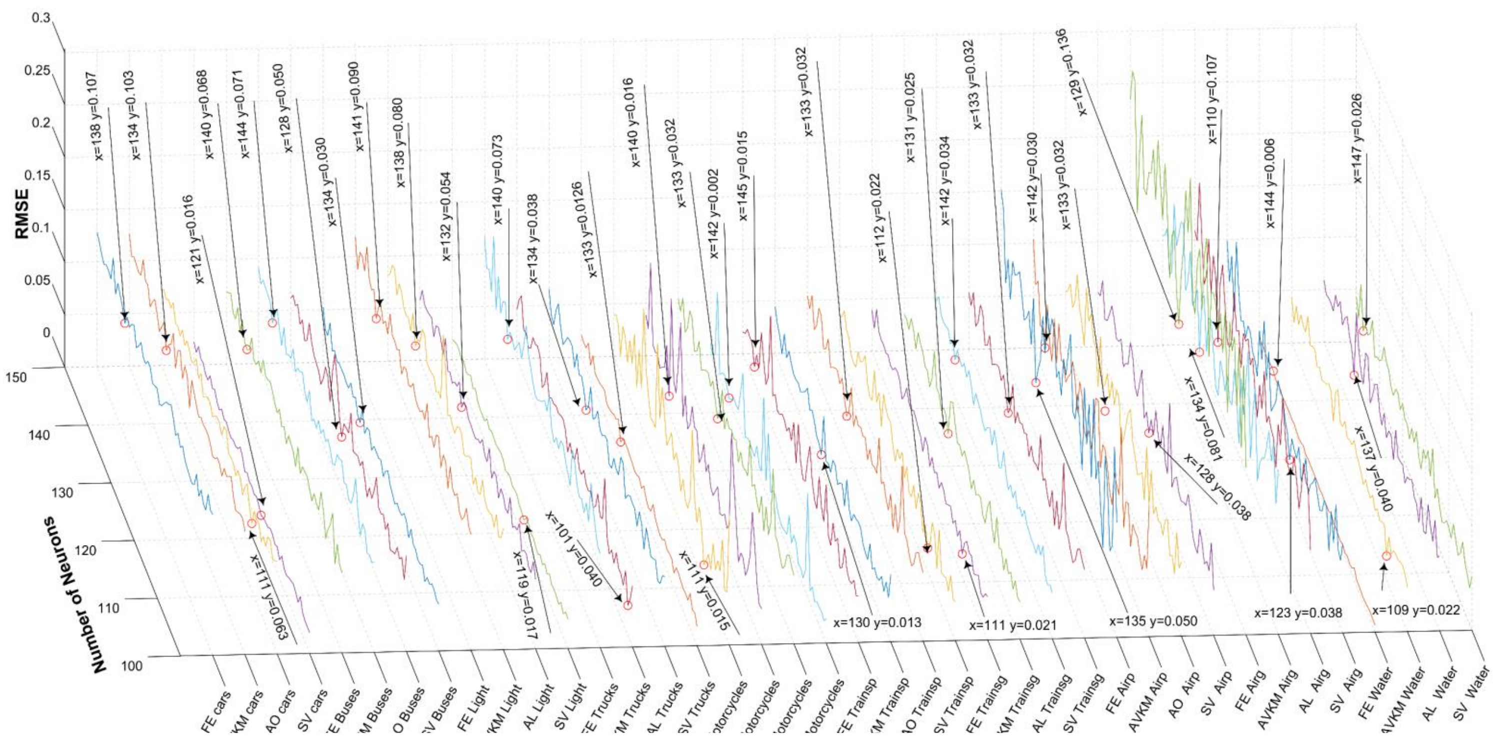

Figure 4 The relationship between the number of hidden layer neurons and the RMSE for each efficiency indicator (with x = Number of Neurons and y = min(RMSE)

was collected. For networks used in vehicles running on more than one type of fuel (the number of outputs varies from one to six), the architecture's RMSE is calculated as the average of the RMSE for each output. The RMSE with the lowest value identifies the optimal architecture. The relationship between N and the RMSE for each efficiency indicator is illustrated in Figure 4. Given the nature and size of the data, RMSE of the 40 networks tested, N was found to be around 100 and 150.

Indeed, it was noticed during this test that networks with a small N had a remarkably high RMSE. This means that the networks are too simplistic at this stage, which results in mediocre prediction simply because the networks are too simplistic and thus incapable of interpolating the relationship between the inputs and outputs correctly. They lack the complexity required to maintain track of the relationship between inputs and outputs. The RMSE decreases as N increases, resulting in relatively minor errors. However, as N increases, the RMSE increases a second, indicating that the networks have become overfitted. Their high complexity and variance make them unsuitable for generalization to unknown data (test sets). Using a large number of neurons to reach the desired prediction is not a great idea.

As illustrated in Figure 4, the RMSE minima for all forty networks fall between 0.2 and 13.6 %, indicating that prediction errors are relatively small. Additionally, only four values of RMSE exceed 10%. (FE cars, AVKM cars, FE air and AL air). All 36 other networks have an RMSE lower than 10%. The figure depicts the required neurons in the hidden layer for each network (parameter x).

To evaluate the model's ability to estimate total energy demand from disaggregated values (energy efficiency indicators), the energy demand values for each sub-sector (road, rail, air, water) were also collected from the ODYSSE database. By employing a bottom-up approach (Equation 8), the energy demand calculated using the efficiency indicators generated by the forty networks could be compared to actual energy values for each country and sub-sector from 1990 to 2019. Figure 5 compares the energy demand of collected data to the data calculated using the bottom-up approach. The R square for each energy demand curve is calculated to perceive the model's prediction quality. The measured data and model curves are very similar in shape for the four sub-sectors.

Indeed, except for Malte's road transport sector (86.3 %), the R square of all curves is greater than 90%. Only Sweden has a lower R square than 95% for rail transport (86.5%). Regarding air transport, the R square of the 28 countries exceeds 95%. The predicted energy demand for the Water mode refers to two R square values below 90% (Luxembourg 87.5% and Lithuania 83.7%). Even though these four values (four curves out of 112) are lower than the average, they are still close to 90%. The findings show the model's excellent prediction performance.

After getting training the 40 networks, the model's performance can be evaluated using completely unknown data. To test this hypothesis, the model is applied to the case study of Morocco, which is an ideal illustration of a complex transportation system without any data on transportation energy efficiency.

Two boundary conditions were taken into account to obtain a realistic prediction of the country's total energy demand. The first assumption is that NGV, LPG, and biofuel are considered to be absent (or nearly absent) from the transportation sector's fuel mix [10]. The second one considers Morocco's lack of progress in integrating electric vehicles into its road infrastructure [62]. In addition, carbon reduction is not a stated priority, resulting in increased reliance on high-carbon modes of transport.

Given that the only available metric for evaluating the model's performance is the sector's total energy demand, the present situation provides an excellent opportunity to evaluate the model's performance. Indeed, because the model employs a bottom-up approach to calculate energy demand at a very disaggregated level, the calculated final energy demand accuracy may attest to the model's ability to generate energy efficiency indicators with precision.

Indeed, the result of calculating the transportation sector's energy demand from 1990 to 2017 (equations (1) to (8)) was compared to IEA data for the same period. As illustrated in Figure 6, the two curves are sufficiently tight while still exhibiting a fair amount of misalignment. Two factors primarily explain this discrepancy: The first may be related to a lack of data on potential fuel leaks, such as those caused by fuel smuggling, which can threaten the measurements of any validated energy consumption estimate. The second factor is methodology-related. Indeed, by using the bottom-up approach, the total error is the aggregate of the model's minor errors for each efficiency indicator.

Nonetheless, the error is tolerable, demonstrating the method's effectiveness at generating coherent energy efficiency indicators. Moreover, these indicators can now be used to describe the entire transportation system in Morocco.

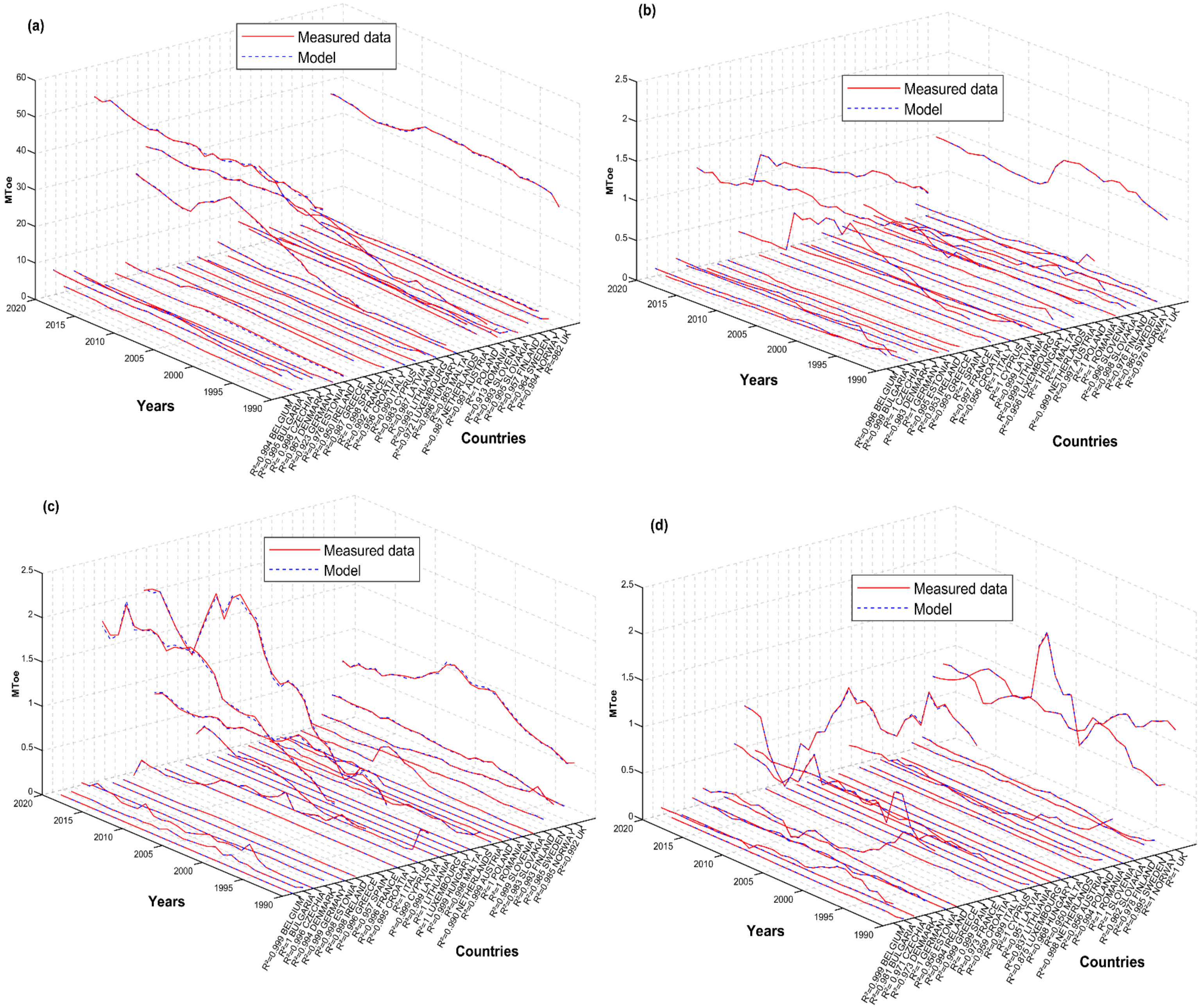

Figure 5 Energy Demand for 28 EU countries (a) Road (b) Rail (c) Air (d) Water

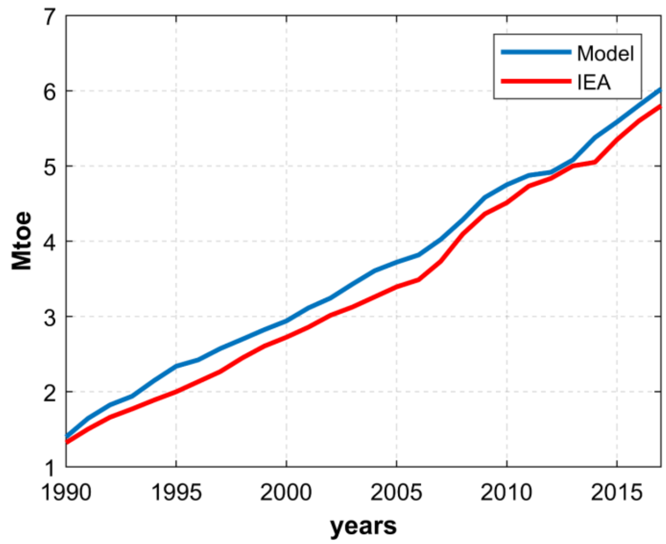

Figure 6 Final transport energy demand (Morocco)

Given the importance of the PKM and TKM indicators for the sustainable development of transportation, it was imperative to analyze the model's results for each vehicle type. Equations (2) and (3) were used to calculate the Moroccan PKM for each vehicle type in 2019. First, the total PKM value is obtained by summing the PKM values for each vehicle. Next, the total TKM for the transportation fret is calculated using the same process (Equations (4) and (5)). Even though Morocco lacks PKM and TKM data for 2019, the model's output (2768 GPKM and 110 GTKM) appears to be consistent with the country's GDP. Indeed, it is remarkable that countries with the highest GDP and population have the highest PKM and TKM values (Figure 7).

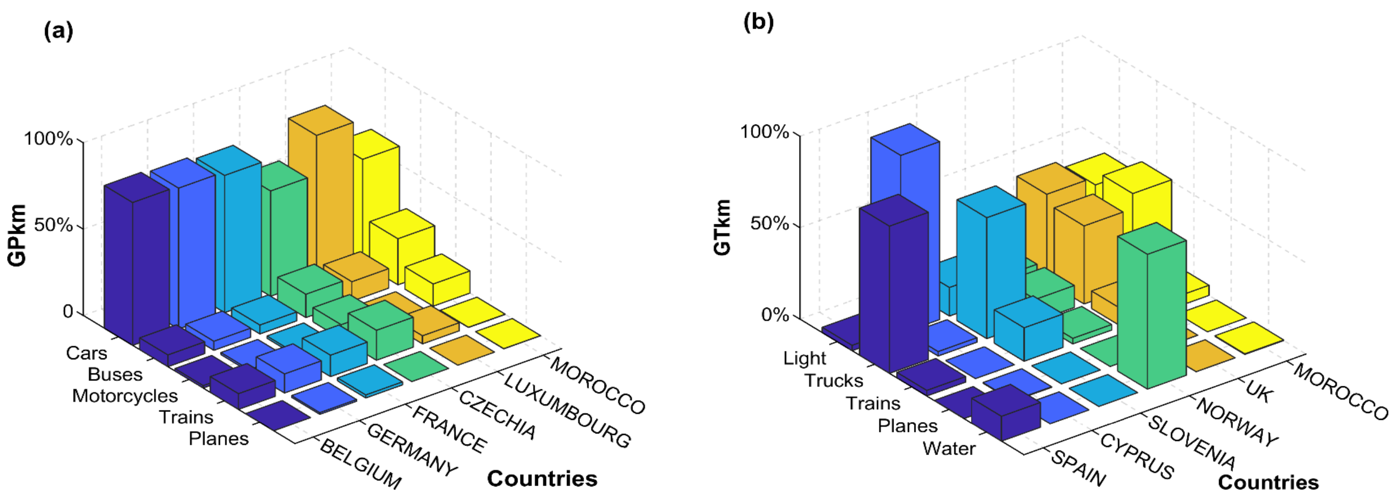

Figure 7: Total (a) PKM and (b) TKM by transport mode in 2019

The variation in PKM may be related to other variables incorporated into the model, such as changes in fuel prices, income, and population density.

As shown in the figure, cars generate the most PKM in all studied countries. However, other modes of transport are used in different ways and for different countries.

TKM generated in Poland is an exceptional case. Poland ranks second in global freight traffic in 2019 with 469 GTKM despite having an average GDP (compared to other EU countries). Indeed, this is explained by Poland's competitiveness and the liberalization of access to the EU's transport market [63].

Additionally, Figure 7 depicts the total PKM and TKM generated per unit of GDP to illustrate the significance of passenger activity and fret required to generate one unit of GDP [17]. The more important the indicator, the greater the effect on the GDP. In 2019, the Moroccan economy appeared to be easily influenced by freight traffic (0.917), following Lithuania (1.194) and Latvia (0.987). Ireland's GDP was found to be the most self-sufficient in terms of freight activity (0.031). For PKM per GDP, the model generated a relatively high index for Morocco (0.841), placing it third behind Bulgaria (1.143) and Croatia (0.840).

The model's PKM and TKM values generation help determine passenger and freight activity distribution among various vehicle types. When the PKM for each type of vehicle is compared between Morocco and five European countries in 2019 (Belgium, Germany, France, the Czech Republic, and Luxembourg), as illustrated in Figure 8(a), cars can be seen as the most frequently used. Belgium, Germany, France, and Luxembourg have high rates of car use (83 %, 82 %, 79 %, and 84 %, respectively). Morocco's PKM generated by cars (60%) is comparable to Czechia's (61%). The contrast between the two countries is apparent in their passengers' use of alternative modes of transport; for instance, while rail is a significant mode of transport for Czechs (17%), Moroccans prefer buses (27%) due to the attraction of this form of motorization, both formal and informal considering the relatively low cost and high frequency of buses in Morocco [62].

As illustrated in Figure 8(b), the five modes of freight transportation vary significantly between countries. Norway, which relies heavily on water for transportation, shows that the country's topography is critical. As is the case in Spain, road infrastructure promotes the use of trucks (80 %). In the case of Morocco, freight is primarily transported by trucks (53%) and light vehicles (51%), mainly attributed to the country's road infrastructure.

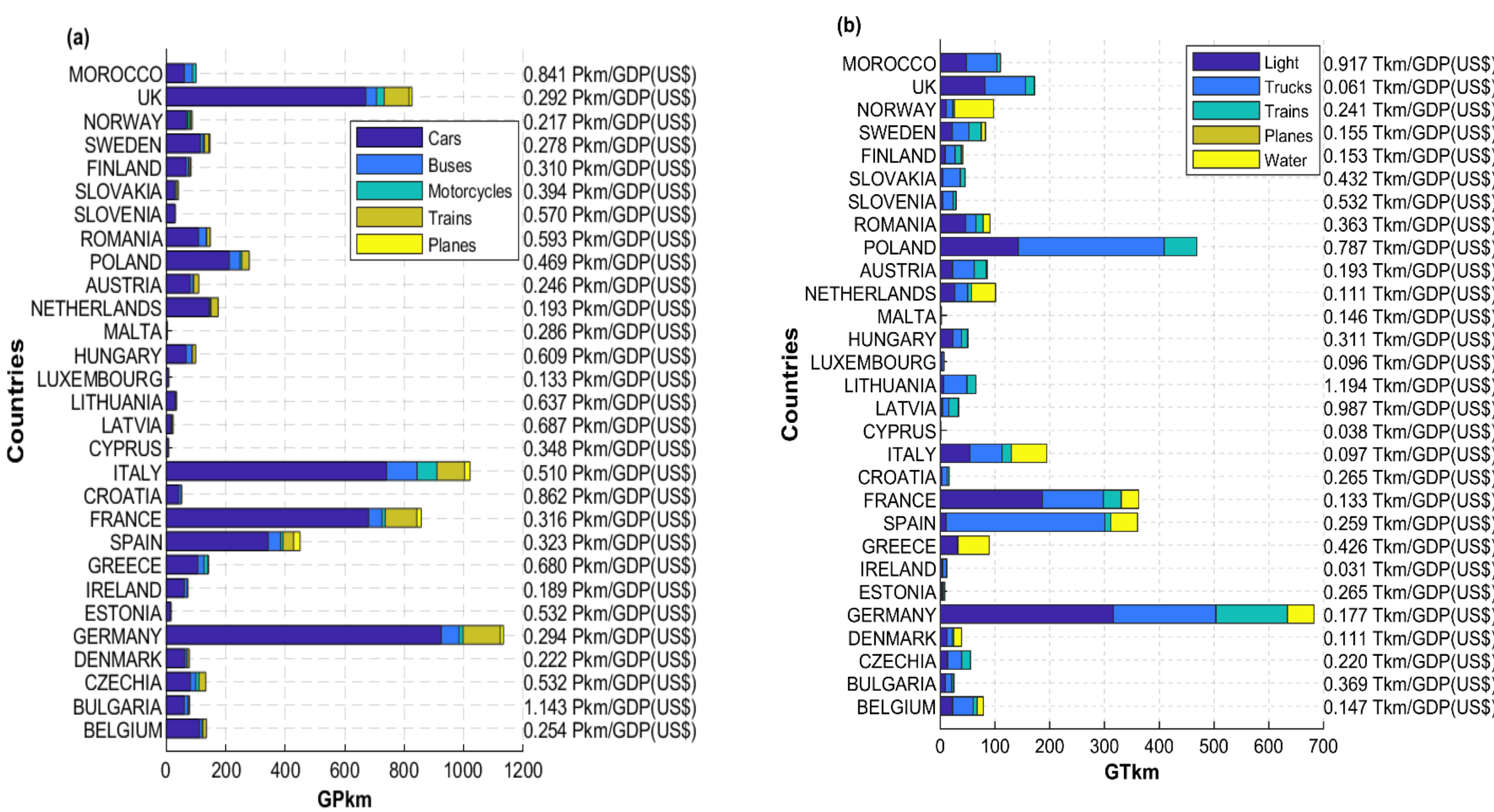

Figure 8: Transport mode share in Total (a) PKM (b) TKM in 2019

4.2. Forecast

Once the model has been trained and validated, it can be used to project the various energy indicators associated with transportation. Consistency of the results in the future is mainly sensitive to the accuracy of the socio-economic parameters forecasted (model input parameters). The population forecast is based on research conducted by the Haut Commissariat au Plan (HCP) [64]. Morocco's population will grow by 29 % in 2050 based on the average fertility variant. For the GDP forecast, the HSBC research study was used [65]. Indeed, their framework took into account a variety of prudent criteria, including demographic growth, education and employment prospects, as well as indicators of democracy. Between 2020 and 2030, average growth rates have been estimated to be 9%, 4% between 2030 and 2040, and 3.9 % between 2040 and 2050. To avoid reverse causality, complexity, and future economic growth issues, the Pump Price Gasoline, Pump Price Diesel, the Price Index, Purchasing Power Parity, Household Final Consumption Expenditure, and Population Density forecasts were calculated using the average growth rates from 2010 to 2020. It is worth mentioning that using the ensemble average growth rate is way too simplistic, whereas the model will produce a more accurate result based on another more concise economic forecasting.

As previously stated, NGV and LPG are not currently included in Morocco's energy mix. However, due to their significant GHG emission factors, the authors have disregarded these two energy sources in the resulting scenarios. Instead, alternatives that are far more sustainable are suggested.

In the absence of clear official forecasting studies, it was essential to formulate a baseline scenario in which the FE of each vehicle type is maintained the same as for 2019. No measure intended to reduce future energy demand is considered. The energy demand is a function of the evolution of the model's eight socio-economic inputs. The business is expected to operate as usual (BaU).

In the second scenario, the FE reduction potentials according to EU legislation [11] were assessed for Morocco's case because more than 85 % of Moroccan transport equipment is imported from Europe (2018).

The third scenario evaluates the gradual introduction of an electric car in the transportation system using a sigmoid function. This function was chosen since electric vehicles are a relatively new product on the Moroccan market. This is an interesting scenario because it examines the potential for energy savings for total electrification of the car's fleet.

The fourth scenario manages to achieve an even higher level of energy efficiency by redistributing the generation of both PKM and TKM through increasing occupancy and load of specific vehicle types. In addition, biofuel is added to the fuel mix of buses and light vehicles to determine its future impact on CO_2 emissions.

Figure 9 depicts four scenarios for the evolution of total energy demand through 2050. Energy demand forecasts are obtained using Equation 8, which involves the disaggregated parameters of the model. Maintaining current trends, energy demand in 2050 may exceed 10,5 Mtoe (74 % higher over 2018).

The estimated demand in scenario 1 relies on the GDP and other socio-economic parameters specified in the model's inputs. Demand may be exceeded if the GDP or population of the country expands at a faster rate. The second scenario considers the implications of the Moroccan government implementing the EU Commission's recommendations. Compared to the baseline scenario, the average FE decreases could result in up to 30% energy savings.

The results of scenario 3 examine the impact of replacing conventional vehicles with electric vehicles using a sigmoid function (equation (17)). The equation's parameters have been chosen for a steady rise to 100% by 2050 (A=1, B=0.5, and C=1). This measure can further reduce energy demand to 7.2 Mtoe (19 % less than scenario 2).

$$S(x) = \frac{1}{(A+e^{-Bx})^{C}} \quad (17)$$

The measures suggested in Scenario 4 are the most energy-efficient. These measures are most visible in the preference for public transportation over private vehicles. Simply replacing trains for trucks has proven an appealing strategy to reduce energy consumption for freight transport transportation.

Given the impact of Total PKM and TKM on the country's GDP as indicated in Section 4.1, keeping these two parameters stable across the three scenarios is beneficial. In addition, energy savings are conceivable by switching out the AO and AL of one vehicle with another. Equations (3) and (5), including AO, AL, AVKM, and SV, indicate that the transportation system will require a smaller SV to generate the same TKM and PKM values.

As illustrated in Figure 10, the forecasting of total PKM is identical for scenario 3 as for scenario 4, reaching 534 GPKM in 2050. However, the distribution of PKM generated by buses and trains has shifted, reducing the one generated by automobiles. Indeed, in Scenario 4, the PKM generated by buses and trains gradually increases. By 2050, it will increase from 92.4 to 239 GPKM. As for buses, PKM generated by trains increases from 0.43 to 59.7 GPKM. To maintain the total PKM unchangeable, PKM generated by cars gradually decreases to 236 GPKM (a significant decrease of 46.5 %).

As illustrated in Figure 11, these results were obtained by recommending an increase in the AO of trains and buses. A sigmoid function is used to enhance the AO in trains. Considering the maximum capacity of trains and buses in Morocco [95], the function's three parameters were chosen to allow for a gradual transition that would result in a maximum average occupancy of 100 seats by 2050 (A=2, B=0.5, and C=1 in Equation) (17). To avoid exceeding the average maximum occupancy of 70 seats on buses, A, B, and C have been assigned 2.3, 0.5, and 1, respectively. If these two types of vehicles continue to provide additional passenger space in the future, significant energy savings are possible.

Likewise, Figure 12 depicts the model's forecasting of total TKM for Scenarios 3 and 4. The TKM is expected to reach 205 GTKM by 2050. This is because trains are now assumed to transport more freight than light vehicles and trucks do. Indeed, due to the trucks and light vehicles amortization, GTKM generated by trains in Scenario 4 gradually increases from 1.2 in Scenario 3 to 73.8 in Scenario 4 by 2050.

By 2050, the TKM generated by light vehicles is expected to decrease by 48 % and 67 % for trucks. Indeed, Figure 13 illustrates how this result is achieved by increasing the AL of trains. The sigmoid function is used to accomplish this progressive increase (Equation (17) for a gradual transition while keeping a maximum AL of 57 t per wagon [95] (A=2.13, B=0.5, and C=1 in Equation) (17)). The inverse sigmoid function described by Equation (18) is used for light vehicles to continue reducing TKM to 50% by 2050 (A=2, B=0.5, and C=1).

$$S'(x) = 1 - S(x) = 1 - \frac{1}{(A+e^{-Bx})^C} \qquad (18)$$

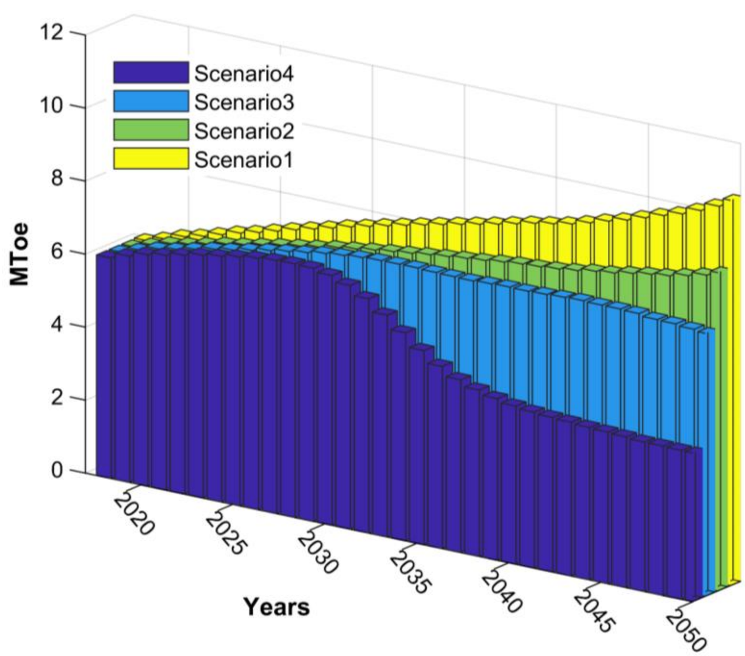

Figure 9: Long-term energy demand for four scenarios

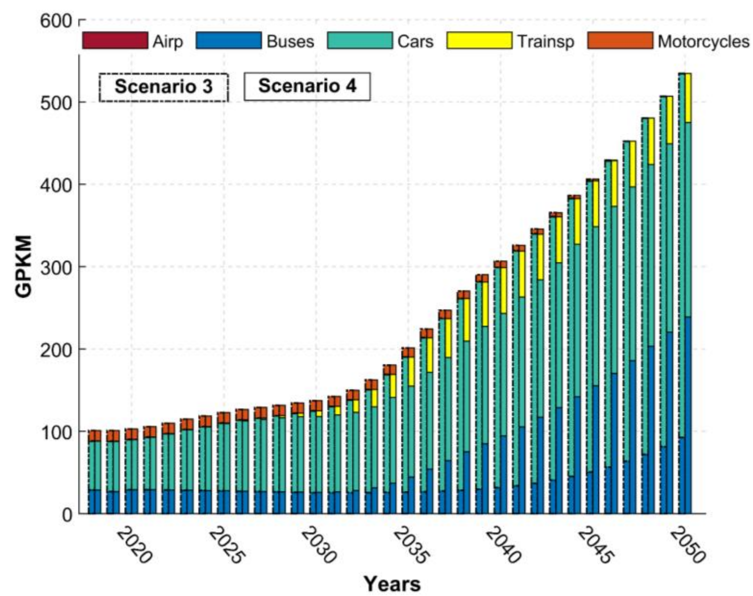

Figure 10: Long-term Total PKM by Transport mode for scenario 3 and scenario 4

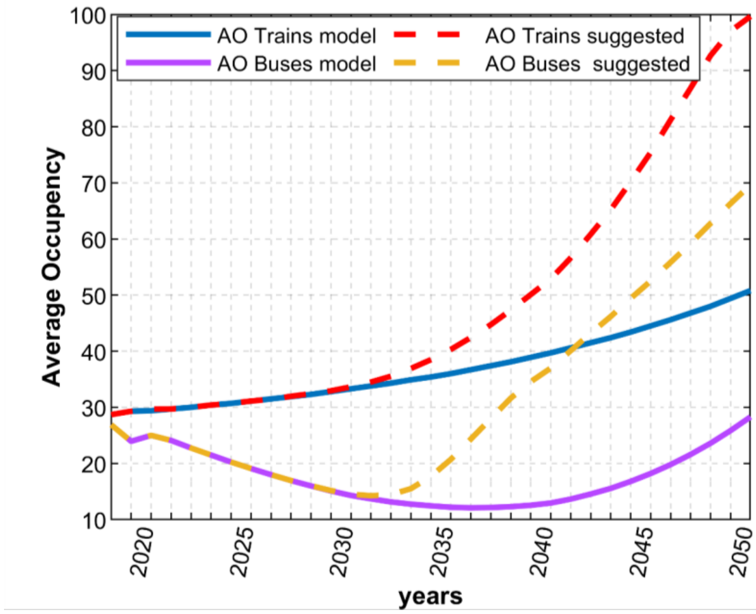

Figure 11: Long term AO with suggested policies for scenario 4

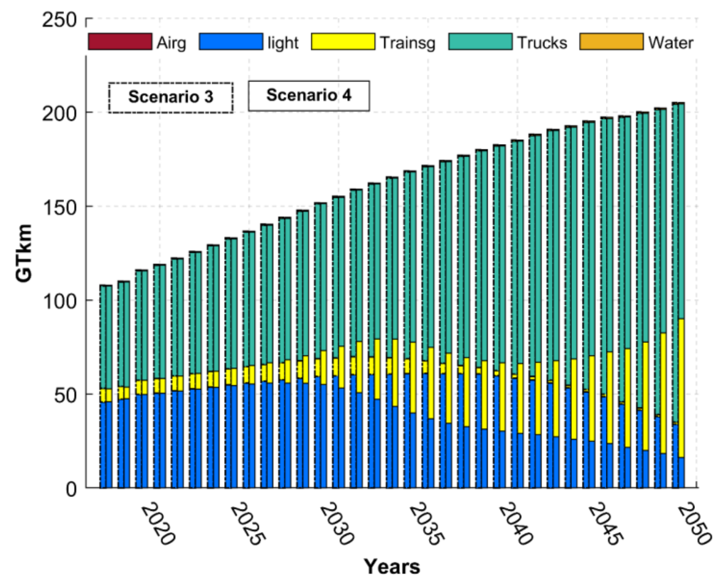

Figure 12: Long-term Total TKM by Transport mode for scenario 3 and scenario 4

Given that those light vehicles require more energy than trucks (due to their lower charging capacity), these two functions initially enabled the switch of TKM generated by light vehicles to freight trains and then the shift of TKM generated by trucks to freight trains.

If future freight transportation technology allows for an increase in Wagons' AL, significant energy savings are achievable.

Considering that carbon dioxide released into the atmosphere during the production of Energy from MSW is considered neutral [66], the impact on CO_2 reduction of introducing biofuel into the fuel mix as a substitute for diesel throughout buses and light vehicles could be assessed. Morocco's biofuel production potential from MSW is estimated to reach 0.95 Mtoe by 2050, based on the country's current MSW production [67].

Figure 14 illustrates how well a sigmoid function (equation (17) with A=1, B=0.235, and C=3) is used to introduce biofuel into the fuel mix while considering the biofuel production limitations imposed by MSW generation. Till 2047, the diesel demand for buses and light vehicles could meet the total amount of biofuel generated by MSW. The additional biofuel that may be produced after this year could be used as a fuel substitute for other modes of transport. More promising solutions for increasing biofuel production may be pursued [68].

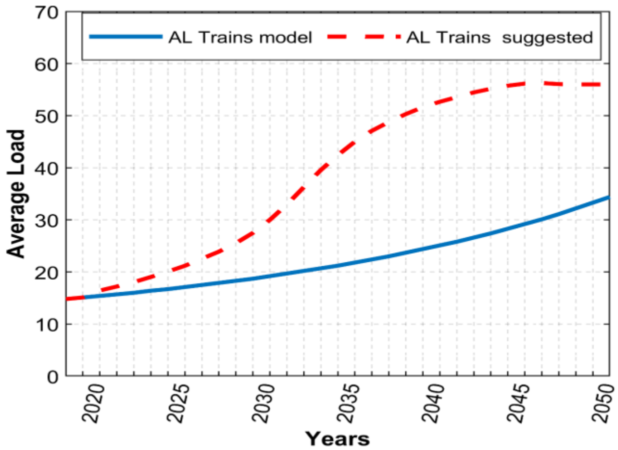

Figure 13: Long term AL with suggested policies for scenario 4

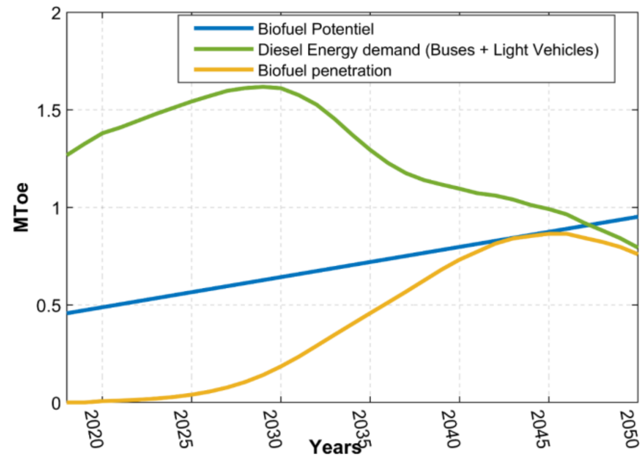

Figure 14: Biofuel penetration in Buses and light vehicles fuel mix

Figure 15 illustrates a comparative analysis of the fuel ratios for Scenarios 4. The diesel in both types of vehicles is phased out as biofuel production increases. As a result, 21% of total diesel is substituted by biofuel. It is important to note that the limit is not technical or economic. Additional innovative solutions may be implemented to increase biofuel production [68].

The GHG emissions of the scenarios are presented in Figure 16 to illustrate the evolution of GHG production, including the global warming potentials of N_2O and CH_4 for each type of fuel (Equation (9)).

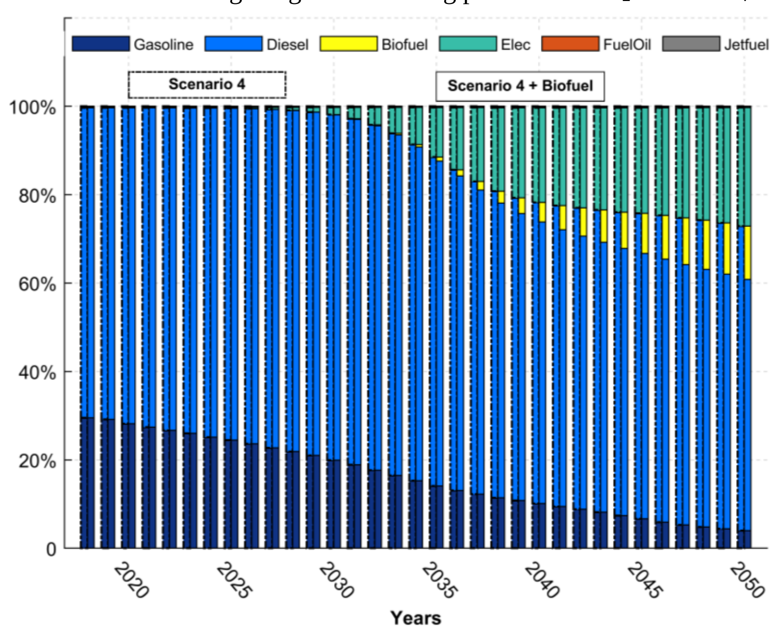

Figure 15:Fuel mix changing share for scenario 4

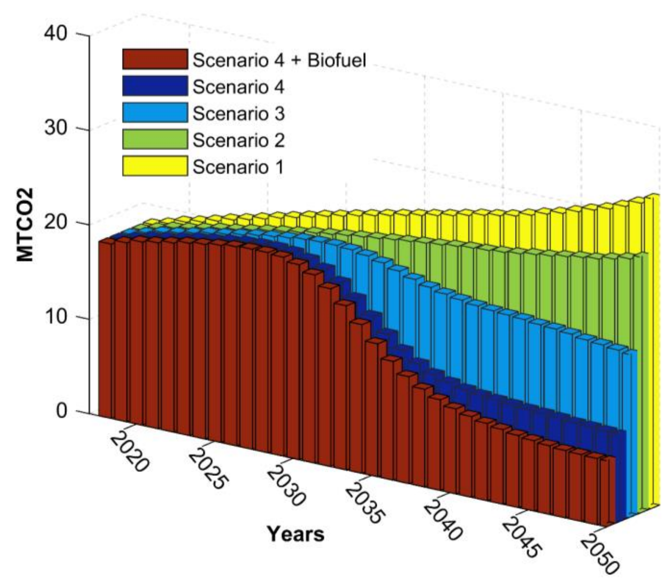

Figure 16: Long-term GHG emissions

When the emissions from the second scenario are compared to the baseline scenario, a 17.4 % reduction is achievable by 2050. Indeed, the Moroccan government will appear to have made significant but insufficient use of EU legislation. For scenario 3, if the entire fleet of cars is electrified by 2050, ten million tonnes of CO_2 could be saved. Nevertheless, It will significantly increase the country's electricity consumption, requiring new infrastructure and technologies. By redistributing the PKM and TKM produced by various vehicles, GHG emissions are reduced by 72%. (9.3 $MtCO_2$). More GHG reduction is conceivable by incorporating MSW-derived biofuel into the transportation fuel mix. Indeed, with 7 $MtCO_2$ estimated for 2050, GHG emissions can be reduced by 24% relative to scenario four without the introduction of biofuel and 79% comparable to scenario 1.

Conclusion

Decision-makers, particularly in developing countries, are frequently constrained by key transportation energy efficiency data. To bridge this issue, a transportation model based on 40 artificial neural networks was built. For 28 European countries, data on energy efficiency indicators were collected to train the model for predicting these indicators using socio-economic characteristics. The model revealed an exceptional ability to generate coherent energy efficiency indicators from socio-economic parameters. To support this claim, ~~To substantiate this assertion,~~ the model was applied Morocco case study, which is an appropriate representation of a complex transportation system that lacks energy efficiency. The model demonstrates its accuracy at generating coherent energy efficiency indicators based on socio-economic data.

Furthermore, thanks to the generated energy efficiency indicators, four scenarios were analyzed regarding energy savings using multiple assumptions:

- Frozen efficiency (BaU): The scenario formulates a baseline considering that no measure is intended to improve efficiency. The results show that energy demand in 2050 may exceed 10,5 Mtoe (74 % higher over 2018).
- Application of EU legislation: This scenario examines the fuel economy requirements according to EU legislation since 85 % of Moroccan transport equipment is imported from Europe. These measures could result in 30% energy savings.
- Cars electrification: The scenario evaluates the gradual introduction of an electric car in the transportation system. This measure can further reduce energy demand to 7.2 Mtoe (19 % less than scenario 2).
- Modal shift: The scenario inspects the redistribution of the transportation of passengers and freight through increasing occupancy and average load capacity, especially for public transportation and freight trains. This scenario revealed a significantly greater potential for energy savings than the first one (61 % less than scenario 1 in 2050). In addition, switching buses and light vehicles from diesel to biofuel was also considered to minimize GHG emissions (79 % less than scenario 1).

Based on the energy efficiency indicators generated by the model, the Moroccan authorities can now realize the most effective ways to reduce future energy demand. It is strongly recommended to encourage the use of public transport in addition to electric vehicles through price incentives and subsidies.

Despite its strengths, the model is limited by the quality of input data and the accuracy of assumptions. The lack of input data, or their low quality, will affect model reliability for estimations and limit the degree to which the model can be expanded. Additionally, more accurate models require technology diffusion elements and physical parameters of the mode/vehicle type. These data may be derived from national surveys or measures, such as those gathered by vehicle registration authorities. To ensure consistent results, it is recommended that modelling exercises should be conducted regularly.

Acknowledgement

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