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# COMPARATIVE ANALYSIS OF FREIGHT TRANSPORT PROGNOSSES RESULTS PROVIDED BY TRANSPORT SYSTEM MODEL AND NEURAL NETWORK

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**Abstract:** This paper deals with problems of processing freight statistic data into the form of time series and analysing consequent results by means of two completely different methods. The first method for calculating chosen transport trends uses the transport model Trans-Tools based on conventional mathematical and statistical functions while the second one uses the scikit learn software providing users with development environment including algorithms of neural networks. The obtained results are similar to a certain extent which shows new possibilities of progressive use of neural networks in future and enables modern approach to analysing time series not only in transportation sector. Comparative analysis of results obtained from the same transport data processed by “standard” mathematical (Trans-Tool) method and neuron-network (scikit learn) method as well as a research focused on some trends development within the scope of freight transport in EU represent goals of this work.

Key words: *comparative analysis, freight transport prognoses, neural networks, Trans-Tools model, scikit learn software, statistics, time series, trends*

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## 1. Introduction

Transportation or, in the reduced sense of the word, its infrastructure can be understood as a central nervous system ensuring communication and transport of both freights and passengers among nodes of a solved area. Together with development of population, industry, and trade also placed demands on transportation increase. To be able to keep up with the development also its *sustainability* must be ensured which represents an exceptionally complex task.

The European Union has tried hard to achieve and ensure economic increase, however, within the following decades, it is necessary to deal with increasing demand for transportation and limited transport infrastructure and, concurrently, to

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ensure a sustainable transport system – “*Creating a sustainable transport system meeting economical, social, and environmental needs of the society represents the goal of the European transport policy.*” (EU 2009, White Book [29]). Not all sustainability aspects in the field of the European freight transportation are of the same importance and, that is why, the prognostic methods included in this article deal only with a subset of the most important ones from the viewpoint of the sustainability (i.e. greenhouse gases emission, dependence on fossil fuels, congestions, and accident rate). Nevertheless, focusing on these criteria does not mean that another criteria as, for example economical and social development, would not be of any significance for the European Commission [16]. To achieve a really sustainable development of freight transportation, it is necessary to elaborate a complex plan based on applied research. Such kind of research had been carried out within the frame of FreightVision project [30] (FP7 EC) managed by AustriaTech company (Vienna, Austria) in which I had been involved in the period of 2009-2010 in a position of a researcher, methodologist, and organizer. Working out a set of recommendation for the Directorate-General for Energy and Transportation of the European Commission<sup>1</sup> how to achieve the sustainable transport system for the above mentioned criteria of sustainability without negative impacts for another criteria represented a goal of the project [1]. The whole project consisted of four basic components: *Visions* (define goals for each of four criteria of sustainability), *Prognoses* (indicate development of the criteria of sustainability; their synthesis is based on key functions used for deriving of key transportation system parameters affecting development of the criteria of sustainability), *Scenarios* (determinate a process aiding to find a way how to achieve the visions at simultaneous taking in consideration achievable development of the key parameters), and *Action plan* (represents finding of a package of measures serving for achievement of a certain set of key parameters or scenario) [23]. The prognoses of freight transport outline different ways of development cause by activities of transport politicians, operators, as well as representatives of industry and commerce [8]. They are based on conditions of common activities (Business-as-Usual) and, aside from technological innovations, do not consider any principal changes. They operate with three different variants: trend prognosis representing the most likely development (obtained by extrapolating available statistical data), low prognosis considering a positive development enabling easier decrease of undesirable factors, and high prognosis at which any elimination of undesirable factors is rather difficult [3]. Forming both low and high prognosis creates a space of all possible development ways while trend prognosis (most likely development) represents values from the middle area. In case of low and high prognoses some parameters can differ a bit considering the trend prognosis – although they are not fully consistent they can be considered as reliable. The prognoses are set up with emphasis on three basic criteria of sustainability: demand on volume of freight transport, demand on modal split, and demand on average load [17]. This work studies and considers possibilities of using artificial neuron networks in the field of transport prognostication by a comparative method of results obtained by help of two utterly different methods: by classic mathematic method represented by Trans-Tool software using standard mathematical and statistical functions and by scikit learn software using neuron network

<sup>1</sup>[https://en.wikipedia.org/wiki/Directorate-General\\_for\\_Mobility\\_and\\_Transport](https://en.wikipedia.org/wiki/Directorate-General_for_Mobility_and_Transport).

algorithms. Aside from that, it brings up-to-date results obtained by processing of actually available statistical data from the field of freight transport within the EU transportation space.

## 2. Methods and materials

### 2.1 Comparative analysis of prognoses originating from different sources

This paper deals with comparative analysis of freight transportation prognoses results obtained by a transport system model and neural networks. For this purpose, forecast results obtained by means of Trans-Tools transport system model within the scope of FreightVision project (FP7) were used for comparison with forecast results obtained by mean of neural networks (scikit learn software) using the same input data (originating from Eurostat statistical database) [4]. Before a proper comparative analysis processing, both the different systems used for forecasting process will be described in detail. Analysing dissimilarities between both sets of results represents the goal of this work because it can bring useful finding about possibility of use of bot the different systems for forecasting purposes namely within the field of transport science [26].

### 2.2 Model of emissions and energy consumption in long-haul transport

*Model structure* – using the model of emissions and energy consumption in long-haul transport is focused on greenhouse gases emissions and fossil fuels consumption as well as other associated factors. There is not an issue of simulation model but of an analytical frame. It helps to create a prognostic view on development of greenhouse gases emissions and fossil fuels consumption in time horizons 2020, 2035, and 2050. The model consists of several series of linear transformations processing emission data from use and production of fuels, demand on fuels for individual kinds of transport, traction technologies, and rolling stock. (Fig. 1) As for mathematic viewpoint, the model is described by linear algebra tools (matrixes) enabling work with model relations between fuel consumption and emission production as well as analysing of structural changes [21]. The model is resolved by means of top-to-bottom method, by sequential aggregating of results of individual technological levels down to general emission and energetic inventory of different kinds of transport and the whole transportation system.

Such the mechanical approach enables more detailed data processing and putting emphasis on nonlinear correlative character of technological impacts interventions. This method prevents analysts from assigning of disproportionate significance concurrently used however opposing technologies (example: in case of increased effectivity of both conventional and ecological engines then general impact would be of less importance than results of development for both categories separately).

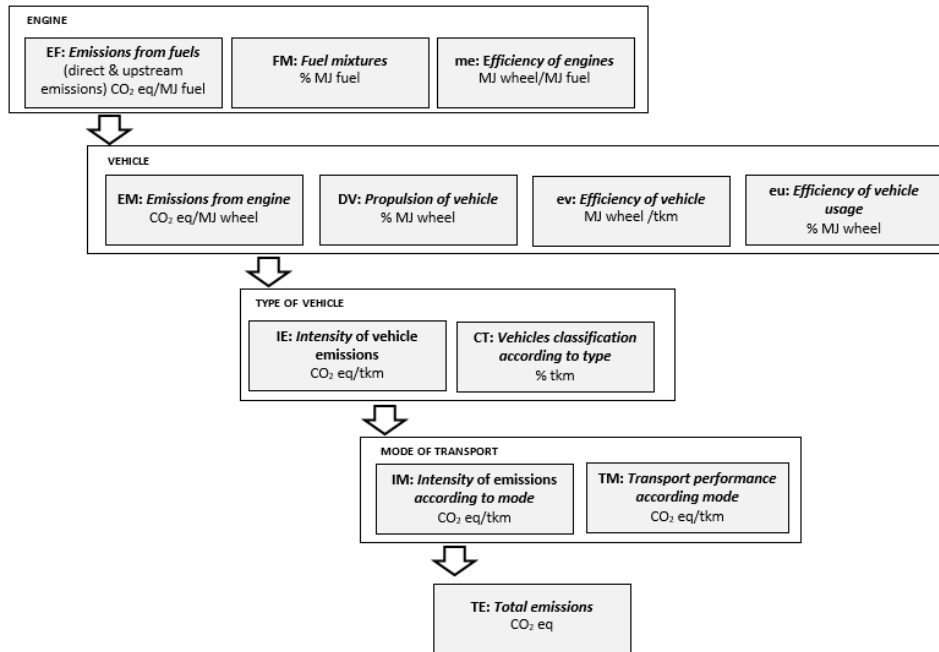


Fig. 1 Emission and energetic structural model (FreightVision).

### 2.3 Trans-Tools transport model

Trans-Tools (Tools for Transport Forecasting and Scenario Testing) developed in 2007 represents a model of the European transport network containing individual, freight, and intermodal transportation. It integrates advanced modelling techniques with interconnecting to modules of economical and commercial activities, logistics, regional development and impacts on environment [10]. Its development was based on the existing up-to-date network model of the European transportation and, aside from its functionality, it met also requests on a system tool with open architecture enabling free access for all developers as well as interested parties. All model components are integrated into the geographical information system ArcGIS (product of company ESRI – Environmental Systems Research Institute) intended for processing spatial data enabling editing, calculating and result displaying (Fig. 2). Linking of individual modules is carried out by means of programme components ArcGIS Model Builder and ArcGIS Geoprocessing Framework. The ArcGIS graphical user interface provide users with more easier displaying, analysing and data processing than most of other transport model.

Trans-tools 3 represents an overall model of the European freight and individual transport and covers an area consisting of 1525 separate zones (originally, 1441 in TT1). Traffic flows are divided according to modes to vehicle, bus, railway, and air. Slow types of individual transport, as cycleways, etc. are not included. Individual transport flows are assigned to networks enabling interconnecting with freight transport flows (number of passenger cars on a road route). Freight trans-

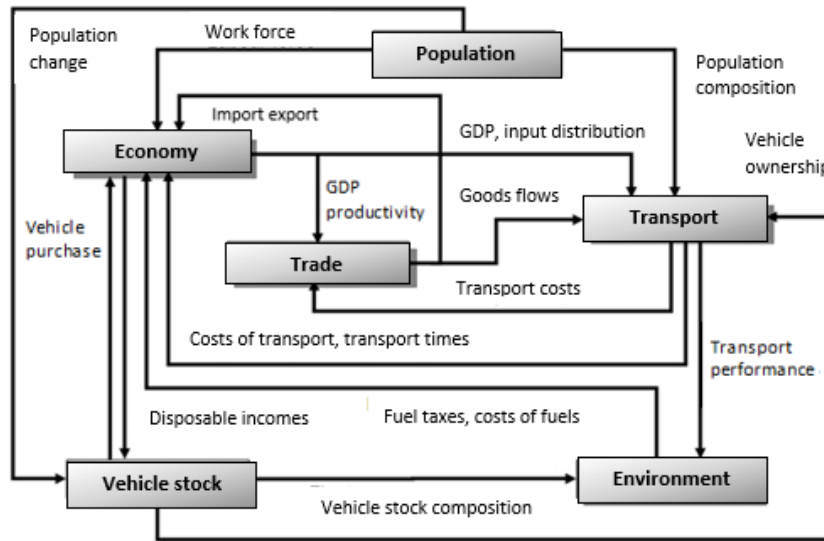


Fig. 2 Spatial arrangement of model data (FreightVision).

port flows are divided according to modes to vehicle, railway, inland and overseas transport [9]. The freight transport model consists of three submodels: *commerce*, *modal choice*, and *logistics*. The commerce submodel calculates amount of tons of future freights produced in every model zone and their distribution among the zones. Amount of tons depends on value parameters of *gross domestic product* while distribution flows from *transport quality* (Level-of-Service; LoS) and *zonal attractiveness*. This submodel provides an input into the modal choice submodel where the tons of freights are redistributed among separate transport types (road, railway, water inland and overseas) based on transport quality [19]. The logistics submodel processes an output of the modal choice submodel and determinates logistic centres and transport chains for the purpose of decreasing logistic costs.

The passenger transport model also consists of three submodels: *generation*, *destination*, and *modal choice*. It is intended for developing prognosis of future transport sample with given parameters. The generation submodel works with categorising of transport operations according to purpose (work, business, or private trips) and parameter values *population change*, *vehicle ownership*, and *gross domestic product* are the most affecting ones (Fig. 3). The destination submodel represents a function of parameters *zonal attractiveness* and *zone accessibility*. Finally, the modal choice submodel processes a modal split prognosis affected by changes of parameter *transport quality* (time and transport costs). All three submodels are interconnected each other, parameter *transport quality* is used for calculating of modal share – further used for aggregation of transport quality data files and input into submodels generation and destination. Further changes in the transport network and congestions affect generation of transport operations. Calculating transport operations according to purpose depends on results of submodels generation and distribution. Basic structure of Trans-Tools model (Fig. 3) [30] in-

cludes three main model components: *passenger transport submodel*, *freight transport submodel*, and *assignment submodel*. Meanwhile, the assignment submodel assigns transported freights and transport operations into the network the *transport quality* structure is being created. Trans-Tools model works with special transport networks and assignment submodels for each transport type separately [25].

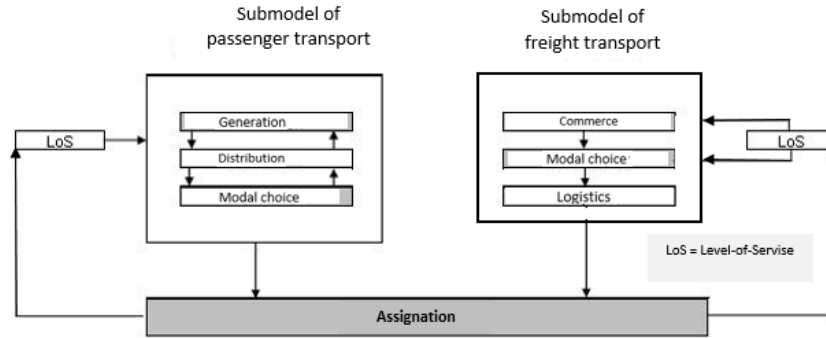


Fig. 3 Basic structure of Trans-Tools model.

Both passenger and freight vehicles are assigned into the transport network concurrently because their affect for congestions is the same. Rout segments include information on velocity and capacity limits. At assigning vehicles to the route segments, their velocity is decreased by recalculating according to curves of traffic flows describing relations between speed, number of vehicles, and transport route capacity. Velocities of transport flows depend on a type of rout communication and on functions derived from research of transport flows. Assigning of impacts of road congestions creates dependence between demands on transport capacity and transport quality (LoS) and appropriate calculations are processed by an iterative method. However, assigning of transport elements at other transport types (railways and inland water ways) does not cause any congestions as in the case of road transport [18]. Fig. 4 [30] depicts the functional structure of transport network model processed within the Trans-Tools environment.

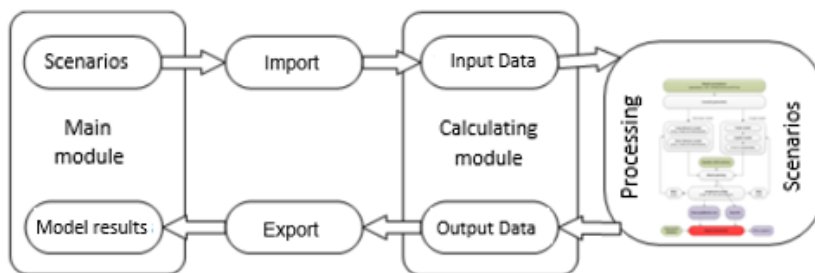


Fig. 4 Functional structure of Trans-Tools model.

By means of Trans-Tools model, it is possible to determine prognoses of transport development within specified time horizons. After input data entering, the

Trans-Tools model creates transport scenarios of future times periods as shown on Fig. 5 [30]. In this article, modules *zonal data*, *transport network and its characteristics*, *costs and logistics* were included. The module *zonal data* requests parameters *population*, *employment*, *vehicle ownership*, *gross domestic product* and *accommodation facilities capacities* as input data. The information is submitted to all 1525 zones of the model. While *population*, *vehicle ownership*, and *gross domestic product* affect type of transport operation, *employment* and *accommodation facilities capacities* represent variables of *zone attractiveness* parameter affecting a choice of a destination.

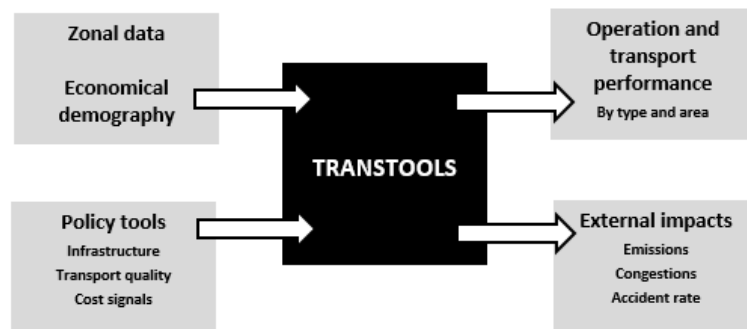


Fig. 5 Model applications.

Modules of transport networks describe an infrastructure used for transporting both passengers and goods. The network enables users to insert new segments or edit existing ones. The route network includes information on route segment length, speed limit, capacity and number of traffic lanes. The railway network includes information on railway segment length, average speed (including time spent in stations), and number of daily trips. The air network includes information on air route length, transport cost, flight duration, and number of daily flights [24]. The inland water network includes information on water route length and average speed (depending on a vessel type).

Costs of using passenger cars include travel costs and road fees. While travelling costs represent a route length calculated by the assigning module and multiplied by the coefficient of average cost per km, values of road fees are saved within the road network characteristics. Travel costs of railway and bus transport connections are given by adjustable cost matrices. Travelling costs of air transport are saved within the air transport network characteristics. Costs of using freight vehicles include route length and trip duration calculated by the assigning module and multiplied by the coefficient of average cost per km and trip duration, values of road fees are saved within the road network characteristics. Also for finding travel costs in case of railway and inland water transport, it is necessary to input coefficients of average cost per km and duration of ride or shipping and to multiply them by length and duration of a trip obtained from the assigning modules. Costs on maritime shipping are saved within an adjustable cost matrix. The loading factor used for individual transport types and commodity groups belongs to main logistic variables. The logistic module includes adjustable input variables (terminal fees for example) [15].

## 2.4 Scikit learn – neural network software

The scikit learn software represents a free software machine learning library for the Python programming language. Scikit learn integrates different components for machine learning and data mining by means its excellent modular data flow processing design. Further, this software represents a competitive method against traditional methods by means of special algorithms representing neural networks. The application uses self-learning using sample data that may contain unknown or hardly expressible inner contexts that can be loaded by noise [6]. Ability of noise filtering and finding of natural development relations belong to its most significant properties for processing of prognostic problems. Multi-level artificial neuron networks represent universal approximating (both linear and non-linear) tool usable for creating a  $n$ -variables function model in the course of learning process based on sample data. For purposes of prognoses creating, it is possible to create differently difficult models, however, solving several basic problems (neuron network configuring, calculating function of neurons, precision of neuron network learning, etc.) is essential for successful use of the neural network [5]. In cases of simpler tasks, there is not need any mathematic prediction model – providing a neural network with a data set used to be enough, the network is able to choice its own model (mostly very appropriate one). The numbers of inputs and outputs are given by a type of neural networks and represent two basic configuration parameters.

A many-layered feedforward neural network with reverse error spread was chosen for predicting of trends developing described in the Section 3. It works on basis of learning with a teacher when sets of historical values (time windows) are put forward successively and results values of the neural network are compared with an estimated output. A classic sigmoid was chosen as a transfer function of input neurons while hyperbolic tangent as a transfer function of hidden neuron layer. An examined time series is divided into training set (80 % of time series), validation set (10 % of time series), and testing set (10 % of time series). Learning of the neuron network was finished when middle quadratic deviation began to increase.

Creating of some approximation model of a multivariable function is essential for using a multi-level neural network [12]. Network configuration (i.e. number of both input and output neurons, total number of neurons, number of neurons in hidden layer, number of hidden layers, and calculating function) affect the model properties. On Fig. 6, there is a scheme of  $n$ -layer network modelling  $O_i(x_1, x_2, \dots, x_p)$  functions.

For prediction, time series of statistical data originating from the period of 2010–2020 were used (Tabs. I–VI). They enabled to carry out learning process of the neuron network on historic data and to evaluate its prediction on testing data. A neuron network with one neuron was found as sufficient one for predicting time series. A learning coefficient  $\alpha$  was set on value 1.

If the neural network consists of  $p$  input neurons,  $q$  neurons in hidden layers, and  $r$  output neurons then, for learning process, the following parameters must be set:

- $q(p + 1)$  parameters between the input and first hidden layer;
- $(n - 3)(q + 1)q$  parameters in hidden layers ( $n \geq 3$ );



- $(q + 1)r$  parameters in output layer.

In total, it means

$$S_n = q(p + 1) + (q + 1)[q(n - 3) + r] \quad (1)$$

$S_n$  is a total number of parameters contained within all layers (input, hidden, and output ones) represented by weights  $W_i$  and thresholds  $\Theta_i$ . The numerous neurons within hidden layers the higher number of parameters and, concurrently, better possibilities of modelling of more complex functions. However, only hidden layer with  $q \geq \min(p, r)$  or  $q = \max(p, r)$  neurons is enough for most of tasks. In the case of equality in the expression  $q \geq \min(p, r)$ , minimizing of number of neurons in hidden layers is ensured, however, network learning may be worse (more learning sessions may be required). For the reason, the expression  $q = \max(p, r)$  should be used in the beginning and, subsequently, a number of neurons or even layers may be decreased or increased. A function of neurons also affects the model properties. For the purpose, the activation functions

$$Y_1(x) = \frac{1}{1 + e^{-x}}, \text{ where } Y_1(x) \in (0, 1) \quad (2)$$

or

$$Y_2(x) = \frac{Y_{\max} - Y_{\min}}{1 + e^{-x}}, \text{ where } Y_2(x) \in (Y_{\min}, Y_{\max}) \quad (3)$$

or

$$Y_3(x) = k \cdot x, \text{ where } k < 1 \text{ (for example } k \approx 0.1) \quad (4)$$

are used.

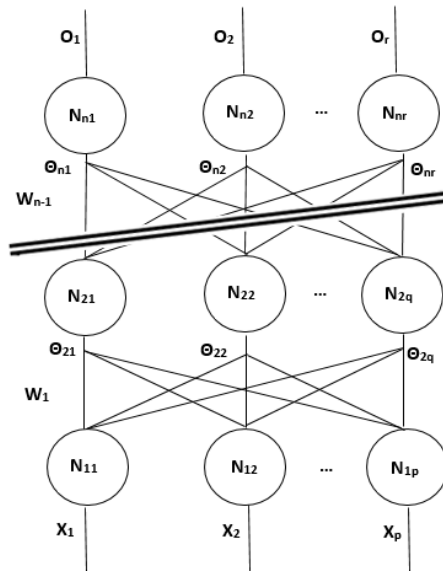


Fig. 6 Scheme of  $n$ -layer network modelling  $O_i$  functions.

To minimize a value of the error function, the method of backward error spreading is processed through learning of the multi-level neural network based on samples (learning with teacher) [13].

$$E = \frac{1}{2} \sum_i \sum_j [Y_j(X_i) - Y_j(X_i)]^2 \tag{5}$$

where  $Y_j(X_i)$  is a required value while  $Y_j(X_i)$  is a real value of the  $j$ -th output at inputs given by the  $X_i$  vector. The learning process is completed when the value of error function  $E < E_0$  (entered value) is achieved when the absolute value of change of the error function for a given number of learning phases is lower than the entered value, i.e.  $\frac{|\Delta E|}{N_e} \leq \delta(N_e - \text{entered value})$  or after completing of requested number of repeating.

A basic trend model is derived from general perspective on behaviour of a system with memory whose outputs are in a given time instance dependent on current inputs and inner states of the system [28].

If  $X = \{x_1, x_2, x_3, \dots, x_p\}$  is the input vector (see Fig. 7) and  $S = \{s_1, s_2, s_3, \dots, s_p\}$  is the vector of system inner states then the system outputs  $Y = \{y_1, y_2, y_3, \dots, y_p\}$  can be considered as dependencies  $y_i(t) = f_i[X(t-1), S(t-1)]$  or  $Y(t) = F[X(t-1), S(t-1)]$ .

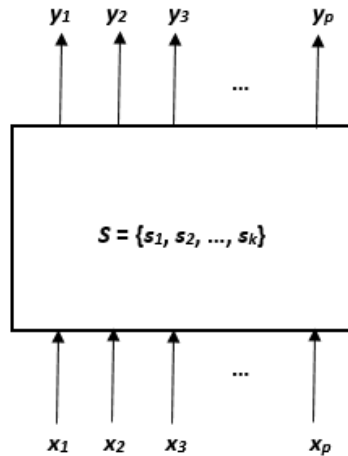


Fig. 7 Scheme of common system.

Generally, time series of multiple outputs or even input parameters (in the form of time series again) can be available for researching of future system behaviour. State values and, in most of cases, also system inputs are unknown and, that is why, they are almost undetectable and, therefore, it is not possible to create any prognostic model in any direct way. In the case of unavailable values of system states and inputs, it is necessary to express the assumption that an appropriate information is included in the output values because each value of output time series is dependent on the system states and inputs. The model function for prediction of future values of time series  $Y$  can be formally expressed as:

$$Y(t) = F[Y(t-1), Y(t-2), \dots, Y(t-k)], \quad (6)$$

where  $k$  represents a number of values of the time series used for prediction of a requested value. The expression (10) is a formal representation of the function of the prediction model with the neural network (see Fig. 8). A default structure of the neural network for this prognostic model contains

$$N_{in} = r \cdot k \quad (7)$$

neurons in the input layer,  $r$  neurons in the output layer, and  $r \cdot k$  neurons in the hidden layer. In the case, not only time series of output values but also input values are available, then it is possible to create the model enabling to research influence of  $X$  inputs on  $Y$  outputs of the system. The formal function of such the model can be expressed as:

$$Y(t) = F[Y(t-1), Y(t-2), \dots, Y(t-k), X(t), X(t-1), X(t-2), \dots, X(t-k)]. \quad (8)$$

Formally, this expression represents a prognostic model shown on Fig. 8. In this

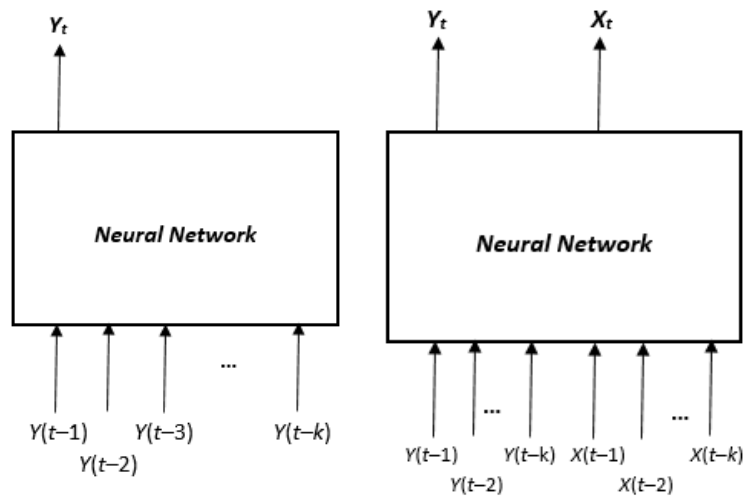


Fig. 8 Basic trend models.

case, the neural network includes

$$N_{in} = (p + r)k + p \quad (9)$$

input neurons; the same number of neurons is contained also in the hidden layer. The expressions (6) and (8) are representatives of structures of learning files of the appropriate models. After learning process, the neural network is used in calculating mode in which one value of  $Y(t)$  outputs is calculated based on the last  $k$  values of time series  $X$  and  $Y$  and  $p$  input values  $X(t)$ . By completing of the calculated values into the appropriate time series, it is possible to carry out

any number of prediction steps and, so, to obtain a development prognosis of an appropriate quantity for longer time period.

The configuration of multi-layer neural networks consist in determining of network inputs and outputs, hidden layers, and neurons in them. The higher amount of parameter the more complex network and, concurrently, possibility of more precise modelling of the requested function defined by a remainder of time series. However, too high value of the parameter need not increase model quality and, vice versa, too lower value may cause excessive filtration – that is why some optimum value at which the model function is the best should be chosen [27]. Mostly, the models based on multi-layer neuron networks with only hidden layer used to be enough. In the case of neuron linear function, a network with only input and output layer is enough because more complex networks can be transformed to the function of such the simple neuron network.

In the phase of learning of the neural network (with determined numbers of neurons in layers and their relations and transformation function) with a teacher, the values of weights and thresholds are progressively set up. After processing of input data, the outputs are compared with the requested outputs and, after that, some corrections (i.e. changes of weights and thresholds) should be carried out to achieve the smallest possible difference between the real and requested outputs. The system represented by time series has a certain “inertia” i.e. the value  $Y_n = Y(t)$  does not notably differ from  $Y_{n-1} = Y(t-1)$ . Then, it is necessary to find such the value of error function  $E$  of neural network learning at which the prediction error  $E_p$  is minimal:

$$E_p = \frac{1}{2}(Y_n^p - Y_n)^2, \quad (10)$$

where  $Y_n$  is the last value of the explored time series and  $Y_n^p$  is the value predicted by the model. By minimizing of the function  $E_p(E)$ , the optimum value (with minimum  $E_p$ ) of neuron network learning is found. If no satisfactory result is achieved, then it is possible to change the value of parameter  $k$ , neuronal function, or even a number of network layers [14]. Then, as soon as information power of a correctly configured neural network achieves a complex level [22] it is able to solve various tasks (as for example forecasting of time series).

Relatively exact results described in Section 3 provided by the neuron network are not too surprising because they are probably caused by current character of the predicted data. Provided the trend data represent regular development, middle deviation can be increasing and low concordance of values changing in testing data can be caused by number of factors (for example underlearning of a neuron network caused by shortage or surplus of training data or by early cancellation of validating process).

### 3. Results and discussion

#### 3.1 Prognoses of freight transport development

Prognoses of freight transport development outline projections of different developmental directions arisen as results of activities of politicians, transport operators, and industry and business agents. They are based on Business-as-Usual (BAU)

activities and do not consider any significant functional changes excepting technological innovations. Usually, they work with three different variation – *trend prognosis* (obtained by means of extrapolation of available statistical data), *low prognosis* (considering positive development enabling easier decreasing of undesirable factors, and *high prognosis* with difficult decreasing of undesirable factors). Creation of low and high prognoses provide a space of all possible ways of development while trend prognosis represents the most probable development and values inside the given transport area. In the case of both low and high prognoses, some parameters may differ in relation to the trend prognosis and, even though they are fully consistent, they can be considered as reliable ones. The prognoses should be created with emphasis on basic sustainability criteria: demands on freight transport volume, modal split, and average load.

Demands on freight transport volume are based on data (in the period of 2010–2020) published in Eurostat (Energy, transport and environment statistics, edition 2020) and increase of demands on freight transport volume with regard to modal split of EU27 countries is considered till 2050. A comparative analysis of prognostical results obtained from the transport model (Trans-Tools 3) and neural network (scikit learn) deals only with *trend prognosis* (both low and high trends are omitted because not represent a subject of this research). The following forecast of transport volume development in mld. tkm. (Tab. I) [24] was calculated by means of Trans-Tools 3 model (rounded to tens of mld. tkm) [4].

Year	Transp. vol. (mld. tkm)	Year	Transp. vol. (mld. tkm)	Year	Transp. vol. (mld. tkm)	Year	Transp. vol. (mld. tkm)
2010	2562	2020	3206	2030	3483	2040	3662
2011	2677	2021	3242	2031	3504	2041	3677
2012	2771	2022	3275	2032	3524	2042	3692
2013	2850	2023	3306	2033	3544	2043	3706
2014	2919	2024	3335	2034	3562	2044	3719
2015	2979	2025	3363	2035	3580	2045	3733
2016	3033	2026	3390	2036	3598	2046	3746
2017	3082	2027	3415	2037	3615	2047	3758
2018	3127	2028	3438	2038	3631	2048	3771
2019	3168	2029	3461	2039	3647	2049	3783

**Tab. I** Forecast of transport volume development in mld. tkm. (transport model).

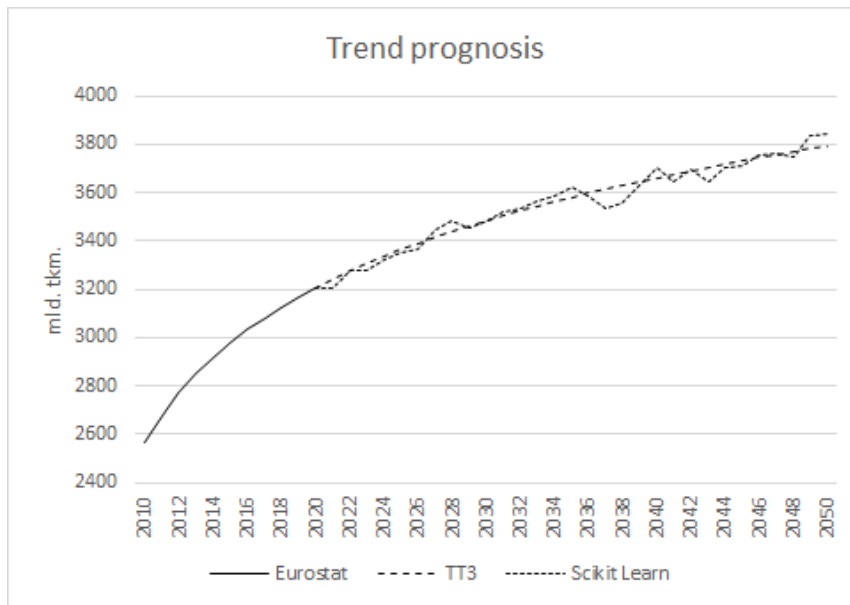
The results based on the same input data obtained by means of neural network – linear function, 2 layers – follow (Tab. II):

### 3.2 Prognoses of amount of greenhouse gas emissions

Forecast of possible development of greenhouse gas (GHG) emissions deals with total CO<sub>2</sub> equivalents figured in tonnes of produced road, railway, and inland water long-distance transport within the EU27 transport space which is considered as

Year	Transp. vol. (mld. tkm)	Year	Transp. vol. (mld. tkm)	Year	Transp. vol. (mld. tkm)	Year	Transp. vol. (mld. tkm)
2010	2562	2020	3206	2030	3481	2040	3701
2011	2677	2021	3207	2031	3520	2041	3646
2012	2771	2022	3276	2032	3534	2042	3697
2013	2850	2023	3276	2033	3568	2043	3643
2014	2919	2024	3320	2034	3584	2044	3703
2015	2979	2025	3355	2035	3625	2045	3709
2016	3033	2026	3364	2036	3588	2046	3755
2017	3082	2027	3446	2037	3539	2047	3763
2018	3127	2028	3480	2038	3560	2048	3747
2019	3168	2029	3454	2039	3633	2049	3840

**Tab. II** Forecast of transport volume development in mld. tkm. (neural network), author’s own research.



**Fig. 9** Comparison of forecast results of transport volume development provided with standard methods and neural network, author’s own research.

the *indicator* for GHG emissions measurement [2]. Production of GHG emission (CO<sub>2</sub> equivalents) originated by long-distance freight transport includes also emissions produced during mining of natural raw materials and fuels production but not emissions caused by infrastructure handling (constructing new roads, railways, etc.).

There are four conditions given for determining of GHG emissions trend prognosis:

- introduction of biofuels continues according to plans;
- till 2050, percentage of non-conventional fossil fuels (oil sands, Diesel fuel distilled from black coal, or oil shale) increases to 30 %;
- peak coal (time instance of maximum volume of coal mining after which reserves gradually decrease) comes around 2035;
- production of electrical energy will match to values determined by backcasting method according to International Energy Agency (IEA, 2020).

### 3.3 Prognoses of fossil fuel share

Decrease of dependence on fossil fuels falls into primary goals of The European Union. Concurrently, the freight transport sector is strongly dependent on sources of fossil energy and fossil fuels. The prognosis shows two trends: demand of total energy and of fossil energy for freight transport sector. Based on the ratio of energetic input of fossil fuels and total energy consumption for long-distance road, railway, and inland waterway freight transport within the transport space of EU27, it is obtained the *indicator* of dependency on fossil fuel share.

The analysis is carried out by the same ways as in the case of the prognosis of greenhouse emission development. Energy from fossil fuels includes all sources of primary fossil energy (natural gas, coal, and oil) consumed in the freight transport sector. Both energy consumed during fuel production and energy contained in proper fuels is included. In the case of electrical energy, sources of fossil energy consumed during electricity production and costs for fuels demanded for electricity production are included. Total energy includes all consumed primary energy including fossil, renewable, and nuclear energy. The indicator is partly limited and expresses only a ratio between two parameters of electricity consumption and, that is why, it does not represent real dependence on fossil fuels. For that reason, fossil fuels and energy consumption are figured in absolute values [16]. There are determined the same conditions for trend prognosis of dependence on fossil fuels as for greenhouse gases emissions. Based on Eurostat data, the following forecasts of total energy demand in million tonnes of oil equivalent (Mtoe) calculated by means of Trans-Tools 3 model and scikit learn SW are figured in Tabs 3.3.1 and 3.3.2 [4].

The following chart (Fig. 10) shows integrated values of total energy demand – statistical data (Eurostat) and predicted data (Trans-Tools 3 and scikit learn neural network SW).

Based on Eurostat data, the following forecasts of fossil energy demand in million tonnes of oil equivalent (Mtoe) calculated by means of Trans-Tools 3 and scikit learn SW model are figured in Tabs 3.3.3 and 3.3.4. [4].

The following chart (Fig. 11) shows integrated values of fossil energy demand – statistical data (Eurostat) and predicted data (Trans-Tools 3 and scikit learn neural network SW).

Year	Total energy	Year	Total energy	Year	Total energy	Year	Total energy
2010	68.10	2020	55.40	2030	51.05	2040	49.07
2011	65.60	2021	54.15	2031	50.80	2041	48.91
2012	65.20	2022	53.68	2032	50.57	2042	48.76
2013	64.50	2023	53.25	2033	50.36	2043	48.61
2014	61.40	2024	52.86	2034	50.15	2044	48.47
2015	61.90	2025	52.51	2035	49.95	2045	48.33
2016	60.00	2026	52.17	2036	49.76	2046	48.20
2017	59.00	2027	51.86	2037	49.57	2047	48.07
2018	57.40	2028	51.57	2038	49.40	2048	47.94
2019	56.50	2029	51.30	2039	49.23	2049	47.82

**Tab. III** Trend forecast of total energy demand in Mtoe (transport model *TT3*).

Year	Total energy	Year	Total energy	Year	Total energy	Year	Total energy
2010	68.10	2020	55.40	2030	51.05	2040	48.27
2011	65.60	2021	54.15	2031	50.00	2041	49.71
2012	65.20	2022	52.08	2032	48.97	2042	47.96
2013	64.50	2023	52.45	2033	51.16	2043	49.41
2014	61.40	2024	51.26	2034	50.95	2044	48.47
2015	61.90	2025	51.71	2035	49.95	2045	47.53
2016	60.00	2026	52.97	2036	48.16	2046	46.60
2017	59.00	2027	50.26	2037	47.97	2047	47.27
2018	57.40	2028	49.97	2038	49.40	2048	47.94
2019	56.50	2029	52.10	2039	49.23	2049	48.62

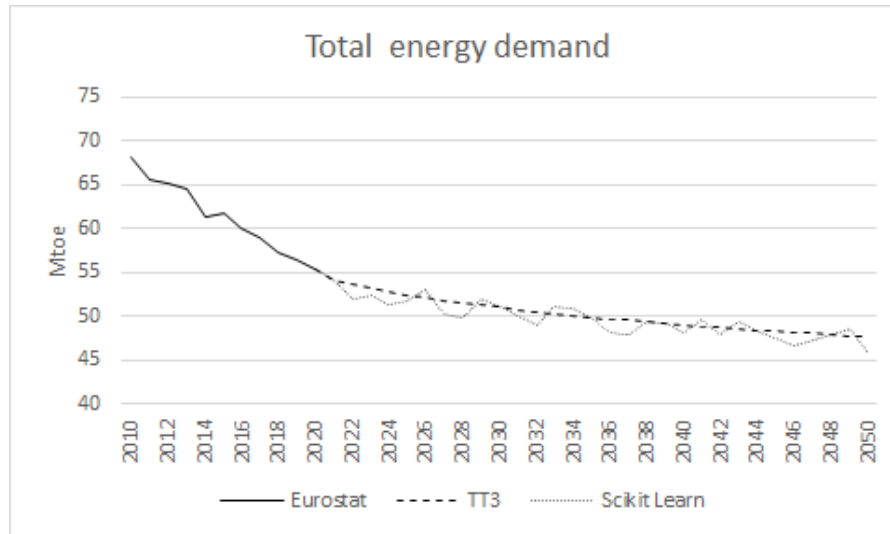
**Tab. IV** Trend forecast of total energy demand in Mtoe (neural network), author’s own research.

In both the cases, the results obtained by processing by means of neural network SW are relatively similar as the ones obtained by standard mathematical-statistical methods.

## 4. Conclusion

At prediction of results of transport processes development, it is not possible to expect absolutely exact answers. Models based on perceptron neural networks substitute paradigmatic states of interpolating functions significantly dependent on network configuration. In many cases, better results are obtained with the configuration wit simple linear function of neurons. Processing the same sets of input data and consequent providing with very similar output values clearly prove





**Fig. 10** Comparison of forecast results of trend forecast of total energy demand provided with standard methods and neural network, author's own research.

Year	Total energy	Year	Total energy	Year	Total energy	Year	Total energy
2010	65.20	2020	62.76	2030	61.53	2040	60.92
2011	64.80	2021	62.56	2031	61.45	2041	60.87
2012	64.40	2022	62.40	2032	61.38	2042	60.83
2013	64.10	2023	62.25	2033	61.31	2043	60.78
2014	63.85	2024	62.12	2034	61.25	2044	60.74
2015	63.60	2025	62.00	2035	61.19	2045	60.70
2016	63.45	2026	61.89	2036	61.13	2046	60.66
2017	63.30	2027	61.79	2037	61.07	2047	60.62
2018	63.10	2028	61.70	2038	61.02	2048	60.58
2019	62.90	2029	61.61	2039	60.97	2049	60.55

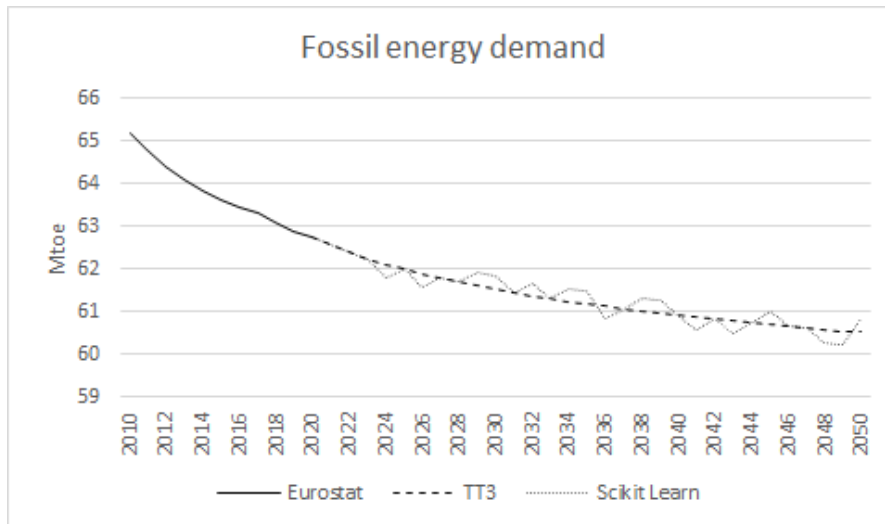
**Tab. V** Trend forecast of fossil energy demand in Mtoe (TT3).

that neural networks can be used for forecasting of development of certain types of freight transport processes in a similar way as standard (mathematic) statistic prognostic methods (used in transport model Trans-Tools) even in very exact science disciplines as for example predicting wear amount of stress areas of transport means [20], engines useful life time, or predicting defective Engines on temporal vibration signals, etc.

Furthermore, neural networks are able to generalize solved problems and are more resistant to noise. On the other hand, there is not possible to exactly determine what did an used neural network learnt and, that is why, it is very difficult to

Year	Total energy	Year	Total energy	Year	Total energy	Year	Total energy
2010	65.20	2020	62.76	2030	61.83	2040	60.92
2011	64.80	2021	62.56	2031	61.45	2041	60.57
2012	64.40	2022	62.40	2032	61.68	2042	60.83
2013	64.10	2023	62.25	2033	61.31	2043	60.48
2014	63.85	2024	61.82	2034	61.55	2044	60.74
2015	63.60	2025	62.00	2035	61.49	2045	61.00
2016	63.45	2026	61.59	2036	60.83	2046	60.66
2017	63.30	2027	61.79	2037	61.07	2047	60.62
2018	63.10	2028	61.70	2038	61.32	2048	60.28
2019	62.90	2029	61.91	2039	61.27	2049	60.25

**Tab. VI** *Trend forecast of fossil energy demand in Mtoe (neural network), author’s own research.*



**Fig. 11** *Comparison of forecast results of trend forecast of fossil energy provided with standard methods and neural network, author’s own research.*

find error estimation [7]. When any description of observed quantity are available then use of neural network may be an ideal way. Evaluation of tools for prediction may be quite complicated because, in the case of statistic procedures, there are ready heuristics available unlike in the case of neural networks where there is no complete heuristics of methods, modelling over processed data, and configuring parameters for individual network types. Within the scope of testing individual parameters, it is impossible to determine some certain network configuration providing with the best results. Quality of prediction carried out by an artificial neural

network is affected by lot of factors with potential positive influence on prediction quality. The factors include number of learning phases, selection of training, testing, and validating set, use of different time series for learning, way of learning, etc [11]. Architectures of neural networks may be easily changed by operators and, so, they enable experimenting with configuration.

Neural networks represent an alternative way to exact statistic (mathematic) methods within the field of forecasting of freight transport development trends as well as within other ones. Quality of prediction of an artificial neuron network is affected by a number of factors that could be of positive influence on predicting quality (for example number of learning cycles, choice of both training and validation set, or use of other time series in the course of learning process. For purposes of this work, a many-layered feedforward neural network with reverse error spread was used although other types of neural networks could possibly provide more exact results.

### List of abbreviations

- BAU – Business-as-Usual
- EC – European Commission
- EU – European Union
- FP7 – 7th Framework Programme (of European Union)
- GHG – Greenhouse gas
- IEA – International Energy Agency
- LoS – Level Of Service (operating conditions of a roadway)
- Mtoe – Million Tonnes of Oil Equivalent
- TT1 – Trans-Tools 1
- TT3 – Trans-Tools 3

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