The Long-Term Development of Transport Emissions in the Czech Republic

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Abstract

Transport is an important element of sustainability but, on the other hand, it causes congestion, accidents, smell, noise, air pollution, health effects etc. This article will focus on the environmental pillar of sustainable transport, specifically on transport emissions. The aim of this paper is to analyze the long-term development of greenhouse gas emissions from transport in the Czech Republic. The paper shows not only trends from last years but although prediction over next five decades will be show in the paper. The long-term development is then compared with the goals of EU transport policy.

KEY WORDS: *transport, greenhouse gases, sustainable development*

1. Introduction

Sustainable transport has become a widely discussed topic in recent years. Generally we can state that sustainable development is an important factor in the development of individual economies. Sustainable transport is characterized as a transport that does not endanger public health or ecosystems, but at the same time it provides for transport demands so that competitiveness and regional development are supported [1]. Sustainable development concept is based on three pillars-the economic pillar, the environmental pillar and the social pillar [2]. The source accentuates the importance of the environmental pillar. Production of greenhouse gases (GHG) is one of the most frequently discussed issues that fall under this pillar in the area of transport; in particular it is the production of carbon dioxide (CO2). CO2 is considered to be the main cause of global warming [3-7]. Transport as a sector is specific by the fact that unlike in other national economy sectors where GHG emission are being reduced, in transport, in particular in individual car transport, CO2 [5] emissions are growing. GHG emissions reduction should therefore become priority number one, however, on the other hand it is essential to mention that this is in contradiction with growing global energy demands [4]. The key factor here is to fully realize that next to the technical aspects also transport behaviour has to change [7-9].

Considering indirect and long-term impacts is very important for the area of sustainable development planning. Thereby analyses of public policies and of related documents are of key importance. On the EU level the key document for this area is White Book of Transport Policy (White Book: Roadmap to a Single European Transport Area – Towards a competitive and resource efficient transport system; hereinafter the White Book) [10]. This White Book is based on the European Commission's vision for transport in year 2050 titled Transport 2050 [11]. On the general level it is essential to reduce GHG emissions by 80%-95% compared to year 1990 level [10] by year 2050. To be able to reach this objective it is essential to cut GHG emissions from the transport area by at least 60% compared to year 1990 level by year 2050. An intermediate stage on this path towards reaching this goal is reduction of GHG emissions by 20% compared to year 2008 level by year 2030 [10]. The Czech Republic (CR) reflected this White Book strategy in its national transport strategy and in year 2013 the CR government passed a document "Transport Policy of the Czech Republic for 2014-2020 with the Prospect of 2050" [12].

The objective of this article is to analyse long-term development of GHG emissions produced by transport in the CR. This analysis shall be executed in two steps:

1. An analysis of the development of GHG emissions produced by transport in the period 1990–2015.
2. Evaluation of GHG emissions development in the context of the goals set in the White Book for years 2030 and 2050. A prediction of future development of this indicator was done under this step.

2. Methods

The following models of Box-Jenkinson's methodology have been used for the prediction of the development of GHG emissions. The B-J methodology is based on both probability and stochastic analyses of a time series where the time series values y_t are explained by the preceding or the shifted values of the time series and by its random components [15]. The basic element in the random quantities [15]. The B-J methodology works with various forecast models; however, most often with Autoregressive Integrated Moving Average Models, that are marked as ARIMA (p, d, q) models and these models are applied for those time series in which there are not any seasons [15]. In case the relevant time series has seasons then, according to the author, for the prediction of the time series is used a more general model – model SARIMA. This model, next to a trend, includes also the above-mentioned seasons [15].

ARIMA(p, d, q) models are defined by the following formula [16]:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t - \vartheta_1 \varepsilon_{t-1} - \vartheta_2 \varepsilon_{t-2} - \ldots - \vartheta_q \varepsilon_{t-q}\,, \quad (1)$$

Chyba! Nenalezen zdroj odkazů.here p – the number of autoregressive terms; q – the number of lagged error terms; ϕ – the coefficients of the autoregressive terms; ϑ – coefficients of the moving average terms and ε_t – white noise process.

Box-Jenkinson‘s methodology includes four steps [16]:

1. Model Identification
2. Guesstimate of Model Parameters
3. Model Diagnostic
4. Calculation of Prediction.

Correct combinations of parameters p, d and q values are selected in the framework of model identification. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are consequently applied for the identification of the model, graphs of these functions respectively. Prior to the calculation of ACF itself and PACF itself estimates it is important to identify any presence of a trend and of „outliers“ observations. Further it is essential to evaluate if it is or if it is not essential to execute transformation stabilizing the range of scatter. However, in the majority of cases it is sufficient to utilize a suitable level of time series differentiation. In this model the desired level of differentiation is labelled as d.

The estimation of parameters for the model that includes estimation of auto regression parameters and estimation of moving average is executed by means of the method of the smallest squares, or possibly by the non-linear method of smallest squares or by the method of maximum credibility that is used most often. The objective of the maximum credibility method is estimation of parameters $\phi_1,\ldots,\phi_p;\vartheta_1,\ldots,\vartheta_q;\mu$ and σ_η^2, where the credibility function reaches its maximum (2), where T is the number of observations after differentiation (3).

$$f\left(a\middle|\phi,\mu,\vartheta,\sigma_\varepsilon^2\right) = L\left(\phi,\mu,\vartheta,\sigma_\varepsilon^2\right) = \left(2\pi\sigma_\varepsilon^2\right)^{-\frac{T}{2}} \cdot \exp\left(-\frac{1}{2\sigma_\varepsilon^2}\sum_{t=1}^{T}\varepsilon_t^2\right) \quad (2)$$

$$T = n - d \quad (3)$$

In the framework of model diagnosis the following is executed: testing of stationarity and seasonality by means of Dickey-Fuller’s test, testing of estimated parameters by means of t-tests, testing of the model as a whole respectively [17]. Consequently residua of the estimated model are tested by means of correlation analysis; in concrete words it is tested whether they might be statistically significant and represent so called white noise process (ε_t) [16]. This represents a sequence of independent random values with the same distribution with zero mean value and with constant spread and that means that errors are distributed evenly according to relations (4), (5) and (6). ε_t is characteristic by its following values of the auto-covariance (7), autocorrelation (8) and partial autocorrelation functions (9). [18]

$$E\left(\varepsilon_t\right) = 0 \text{ for } t = 1,2,\ldots,n \quad (4)$$

$$D\left(\varepsilon_t\right) = \operatorname{var}\left(\varepsilon_t\right) = \sigma^2 \text{ for } t = 1,2,\ldots,n \quad (5)$$

$$\gamma_k = C\left(\varepsilon_t, \varepsilon_{t-k}\right) = 0\,,\ k \neq 0 \quad (6)$$

$$\gamma_k \begin{Bmatrix} \sigma_{\varepsilon_t}^2 & k = 0 \\ 0 & k \neq 0 \end{Bmatrix} \quad (7)$$

$$\rho_k \begin{Bmatrix} 1 & k = 0 \\ 0 & k \neq 0 \end{Bmatrix} \quad (8)$$

$$\phi_{kk} \begin{Bmatrix} 1 & k = 0 \\ 0 & k \neq 0 \end{Bmatrix} \quad (9)$$

In case all conditions are fulfilled, it is possible to use the estimated model for the prediction of time series. In the opposite case it is essential to come back to the model identification step and to repeat the entire process.

In case of some time series there may happen that two or more models suitable for these time series can be identified. The most suitable model is always the one that minimizes the criteria value. It is possible to use the following criteria: Akaike Information Criterion (AIC) (10) [19, 20], The Akaike Information Criterion with a correction, (AICc) (11) [21, 22] and Bayesian extension of Information Criterion (BIC) (12) [23]. Criteria do not cause any distortion as for instance the determination index in classical regression.

$$AIC(M) = T \ln \hat{\sigma}_{\varepsilon}^2 + 2M \tag{10}$$

here T – the number of observations after differentiation, M – the number of parameters $M = p + q$, $\hat{\sigma}_{\varepsilon}^2$ – residual scattering of the observed time series.

$$AICC(M) = \ln \hat{\sigma}_{\varepsilon}^2 + \frac{\dfrac{2M}{1 - \dfrac{(M+1)}{T}}}{T} \tag{11}$$

$$BIC(M) = T \ln \hat{\sigma}_{\varepsilon}^2 - (T - M) \ln\left(1 - \frac{M}{T}\right) + M \ln T + M \ln\left(\frac{\dfrac{\hat{\sigma}_x^2}{\hat{\sigma}_{\varepsilon}^2} - 1}{M}\right) \tag{12}$$

here $\hat{\sigma}_X^2$ – selection scattering of the analysed time series.

The probability calculation phase includes in itself also the calculation of the forecasts and of their reliability intervals. General forecast $\hat{X}_n^*(h)$ is illustrated by the relation (13), where h is the horizon of the forecast [16]. In case that $h > p$ and $h < q$, the forecast can be written in the following way (14). The reliability intervals for forecast of time series $\hat{X}_n^*(h)$ is calculated by relation (15) where is valid (16) [16].

$$\hat{X}_n^*(h) = \hat{\phi}_1 \hat{X}_n^*(h-1) + \ldots + \hat{\phi}_h \hat{X}_n^* + \ldots + \hat{\phi}_p \hat{X}_{n-p+h}^* - \hat{\vartheta}_h \hat{\varepsilon}_n - \ldots - \hat{\vartheta}_q \hat{\varepsilon}_{n-q+h} \tag{13}$$

$$\hat{X}_n^*(h) = \hat{\phi}_1 \hat{X}_n^*(h-1) + \ldots + \hat{\phi}_p \hat{X}_n^*(h-p) \tag{14}$$

$$C_n = \hat{X}_n^*(h) \pm c \sqrt{\left(\sum_{j=0}^{h-1} \hat{\psi}_j^2\right)} \hat{\sigma}_{\varepsilon} \tag{15}$$

$$\sum_{j=0}^{\infty} \psi_j^2 = \infty \tag{16}$$

3. The development of GHG emissions produced by transport in the CR in the period 1990–2015

The development of GHG emissions produced by transport in the CR (measured in million tons CO2 equivalent, MT of CO2eq) illustrated in Fig. 1, can be grouped into three periods. In years 1990–2007 (with the exception of year 1991 – decline by 0,89 MT of CO2eq and 2000 – decline by 0,05 MT of CO2eq) GHG emissions increased 256,6 %; from value 7,28 MT of CO2eq in year 1990 up to value 18,69 MT of CO2eq in year 2007. The biggest increment in emissions was in years 2003 (1,77 MT of CO2eq) and 1992 (1,58 MT of CO2eq). In year 2007 transport produced the largest volume of GHG emissions – 18,69 MT of CO2eq - which represents nearly 2,6multiple of the 1990 value. In the second period, that means in years 2008-2013, GHG emissions showed a declining trend; from value 18,56 MT of CO2eq in year 2008 the volume of emissions declined by 11,4 % and reached the volume of 16,43 MT of CO2eq in year 2013. The largest year-on-year decline (1,01 MT of CO2eq) was observed in the period 2009 to 2010. In the last two observed years we can see a growing trend-the volumes grow; in year 2014 by 0,54 MT of CO2eq up to the volume of 16,97; in year 2015 by 0,78 MT of CO2eq up to volume of 17,75 MT of CO2eq. In year 2015 GHG emissions got up to the level of year 2006.

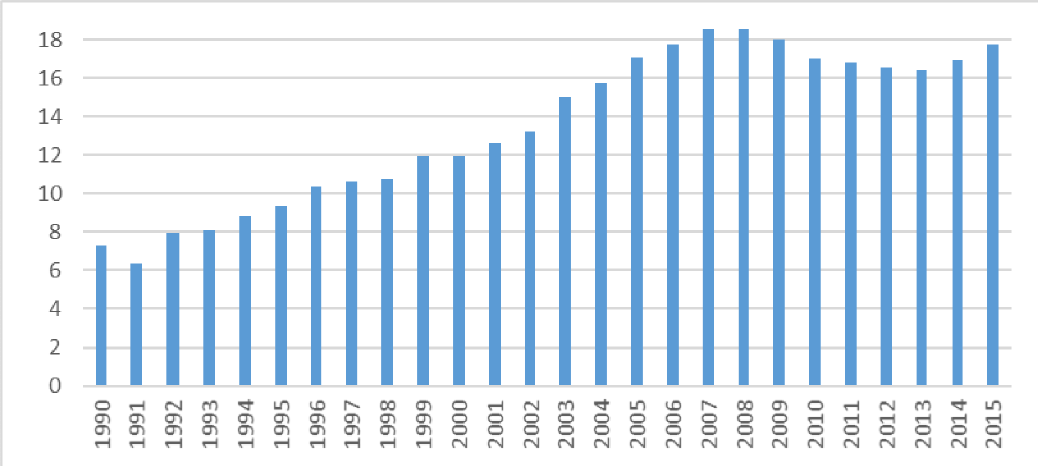

Fig.1 The development of GHG emissions produced by transport (MT of CO2eq) [24]

4. Prediction

For time series modelling, R software (the R Project for Statistical Computing) was used. In R software all steps required in ARIMA modelling are contained in a function auto.arima(), which returns best ARIMA model according to either AIC, AICc or BIC value. The function conducts a search over possible model within the order constraints provided. Considering the emission data are annual and there appears to be no seasonal pattern, a non-seasonal ARIMA model was selected. For modelling there was selected ARIMA(2,1,0) model with non-zero mean or just AR(2) model including intercept:

$$y_t = 0{,}1295\Delta y_{t-1} - 0{,}5617\Delta y_{t-2} + \varepsilon_t \tag{10}$$

$$\Delta y_t = y_t - y_{t-1} \tag{11}$$

here Δy_t – the first time difference (11):

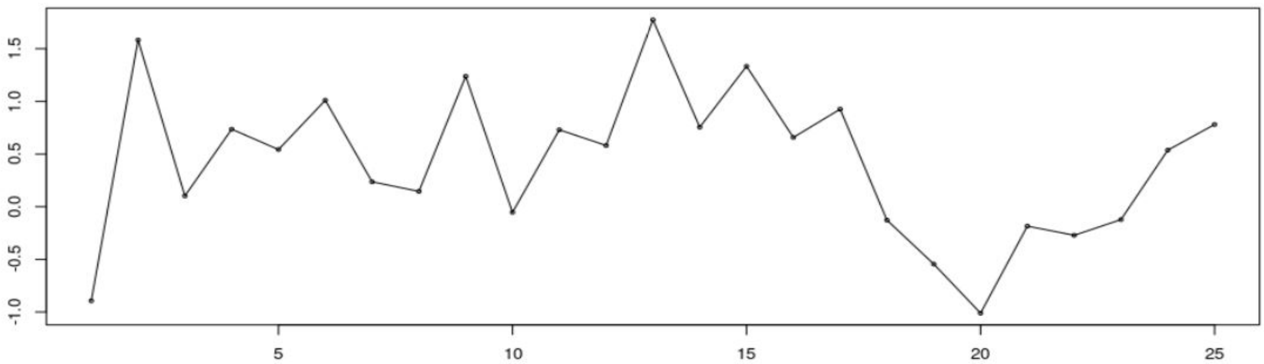

Fig. 2 The line chart of the analysed time series

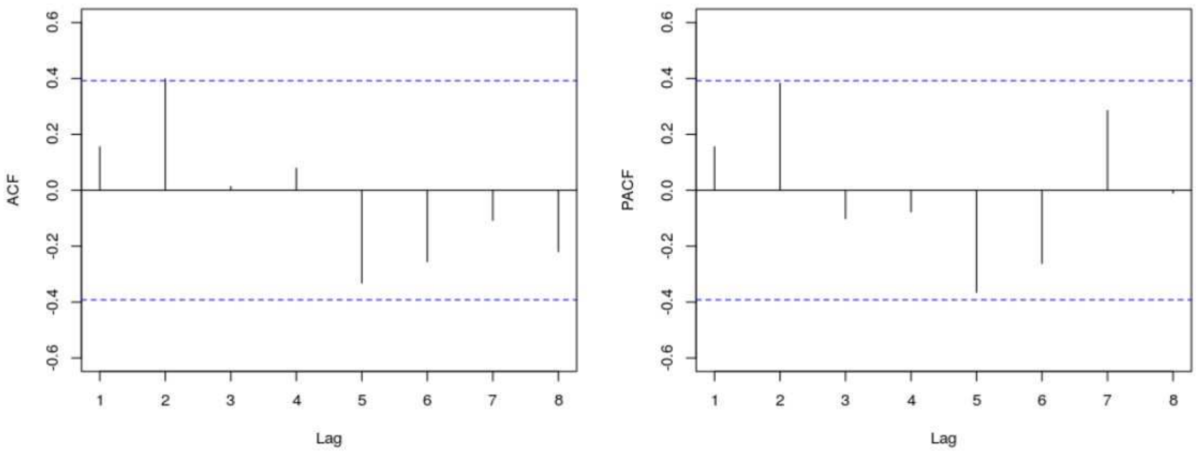

Fig. 3 ACF and PACF functions visualisation

In Fig. 2 and Fig. 3 there are illustrated basic characteristics of a time series. Fig. 2 shows basic line chart of the analysed time series (their differences respectively). In Fig. 3 we can see visualisation of ACF and PACF functions. These functions can be utilized for identification of a suitable model and they are on top of this also a suitable model tool for evaluation of time series stationarity.

In case of the observed time series the suitable model was selected based on information criteria (Table 1). BIC was taken as the key decision point. ACF and PACF functions were considered primarily for verification of the hypothesis of stationarity. In our research however the main tool for confirmation of the stationarity hypothesis remains to be tests specifically designed for these purposes. One of the most important indicators of no-stationarity time series is that majority of ACF and PACF values oscillate around the value 1, however in our case this does not represent any problem.

Table 1

Values of the criteria

AIC	56,14
AICc	57,28
BIC	59,8

The result of the prediction of GHG emissions development with time is illustrated in numbers in Tab.2 and it is graphically illustrated in Fig.4. Concrete values of the prediction of GHG development, calculated by means of ARIMA model, are defined by the top and the bottom borderlines of the given confidentiality interval. Calculations were done for reliability levels of 80%.

Tab.2 summarizes forecasted values for key years 2030 and 2050 to which the transport policy goals in the area of GHG emissions are related.

Table 2

GHG emissions produced by transport in the CR – outputs of the ARIMA model (MT of CO2 equivalents)

Year	The mean Value	Low 80	High 80
2030	20,34	11,96	28,72
2050	20,47	1,96	38,99

Fig.4 shows forecast of development of GHG emissions calculated using the ARIMA model. Charts are executed separately for the forecast till year 2030 and for year 2050. Results for HGH emissions forecast for year 2030 show values with higher level of reliability.

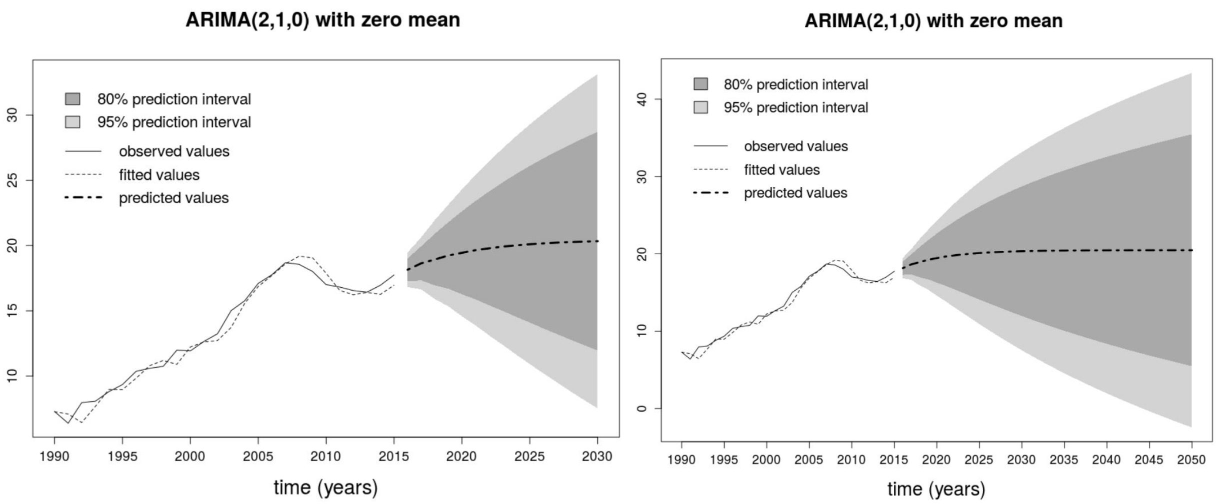

Fig. 4 The forecast till year 2030 and 2050

3. Conclusions

A development analysis of GHG emissions produced by transport between years 1990 and 2015 was executed in this article. In this period there was a significant increase in the total volume of GHG emissions, however this increase is not continuous throughout the period. Based on the data from the observed period a prediction of possible GHG emissions development till the year 2050 was made. The prediction was created by using the Box-Jenison's methodology, specifically using the ARIMA model. The results of the prediction do not show any decline which was set in the White Paper. It is important to mention that this prediction is based on the current situation; however, it takes into account many deviations from the current state probably caused by introduction of suitable measures to reduce GHG emissions or by increasing GHG emissions due to unexpected effects.

According to the White Paper provision, at least 60% reduction of GHG emissions is necessary to be made in the transport sector till the year 2050 compared to the year 1990, which represents a value of 3,14 MT of CO2eq. Reduction of GHG emission by 20% below the level of year 2008 (representing the value of 14,85 MT of CO2eq) is an intermediate stage in achieving the ultimate goal. It is impossible to reach this intermediate stage in case that no measures for a GHG emissions reduction would be introduced (the median value calculated by ARIMA model for the year 2030 is 20,34 MT of CO2eq). Meeting the goals set for year 2050 requires a much more dramatic reduction of GHG emissions, especially due to the fact that the above mentioned 60% GHG emissions reduction is related to year 1990 (when the level of GHG emissions was less than half of the year 2008 level). GHG emissions should be perceived as a major problem of contemporary society which is needed to be solved for human future on the Earth, so all the scientific skills should be fully involved.

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