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RESEARCH ARTICLE

Modeling of policies for reduction of GHG emissions in energy sector using ANN: case study—Croatia (EU)

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Abstract This study describes the development of tool for testing different policies for reduction of greenhouse gas (GHG) emissions in energy sector using artificial neural networks (ANNs). The case study of Croatia was elaborated. Two different energy consumption scenarios were used as a base for calculations and predictions of GHG emissions: the business as usual (BAU) scenario and sustainable scenario. Both of them are based on predicted energy consumption using different growth rates; the growth rates within the second scenario resulted from the implementation of corresponding energy efficiency measures in final energy consumption and increasing share of renewable energy sources. Both ANN architecture and training methodology were optimized to produce network that was able to successfully describe the existing data and to achieve reliable prediction of emissions in a forward time sense. The BAU scenario was found to produce continuously increasing emissions of all GHGs. The sustainable scenario was found to decrease the GHG emission levels of all gases with respect to BAU. The observed decrease was attributed to the group of measures termed the reduction of final energy consumption through energy efficiency measures.

Keywords GHG emissions · Artificial neural network · Energy consumption · Energy sector

Introduction

The world of today faces global warming and climate changes as one of the most severe problems. A relatively rapid increase of global temperature is affecting most of the world ecosystems and is threatening with the possible extinction of species that are unable to migrate or adapt fast enough (Brierley and Kingsford 2009; Ridgwell and Valdes 2009). Also, the extreme weather conditions became very frequent recently and are occasionally causing elementary disasters that take human lives and can severely affect economies of the stricken countries.

The emissions of greenhouse gases (GHGs), especially of carbon dioxide (CO_2), are considered as the main cause of global warming (Soytas et al. 2007). Yet, the global energy system is still dominated by fossil fuels whose combustion accounts for 80% of anthropogenic GHG emissions; this is the largest individual human influence on climate (Quadrelli and Peterson 2007). Therefore, solving the problem of GHG emissions and diminishing their impact on environment became an important issue for researchers and policy makers in a large number of countries, especially the highly developed ones. The United Nation Framework Convention on Climate Change (UNFCCC) in 1992 and Kyoto Protocol in 2005, as the extension of UNFCCC, were the first and probably the most important global efforts to mitigate GHG emissions. After them, many other conferences were held involving negotiations about the reduction of GHG emissions. Yet, along with the climate change combat, the economic growth still remains a priority for national governments (Nader 2009). Accordingly, their policy focuses on the sustainable development. This term, which arose in the 1980s, implies human

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welfare in equilibrium with environmental management (Cobbinah et al. 2015).

Estimation of GHG emissions plays an important role in decision making and planning of the energy consumption per sector. For that purpose, diverse approach is applied (Antanasijević et al. 2014; Chamberlain et al. 2011; Chitnis et al. 2012; Del Prado et al. 2013; Pukšec et al. 2014; Sarica and Tyner 2013). Artificial intelligence, especially artificial neural networks (ANNs), seems to be very popular; ANNs were successfully applied for modeling of various phenomena (Bolanča et al. 2005, 2008, 2009). ANNs are a good alternative to different solutions used in environmental decision (Matthies et al. 2007). ANNs do not need a rigid mathematical model, and the calibration parameters can be developed using data through training or learning process. ANNs are considered as standard nonlinear estimators (Despagne and Massart 1998), and their predictive and generalization abilities have been demonstrated through their successful applications in variety of fields (Gardner and Dorling 1998; Fernando et al. 2012; Singh et al. 2012; Hájek and Olej 2012; Russo et al. 2013). In the last decade, ANNs have arisen as an alternative approach for estimating emissions of various pollutants (Raimundo and Narayanaswamy 2001; Alonso et al. 2007; Lim et al. 2007; Khoshnevisan et al. 2013; Antanasijević et al. 2013, 2014; Stamenković et al. 2016). The main difference between the emission factor method and the ANN approach is that the ANN approach requires a significantly smaller number of input parameters and they are widely available, even for countries where emission-related data is scarce (Stamenković et al. 2016).

ANNs were successfully applied for the prediction of NH_3 concentration in the air (Raimundo and Narayanaswamy 2001) and NH_3 emissions from a field-applied manure (Lim et al. 2007), as well as for the estimation of the annual emissions of other air pollutants, e.g., PM10 (Antanasijević et al. 2013) and greenhouse gases (Antanasijević et al. 2014). Several studies have shown that sustainability and economical/industrial parameters are suitable for the creation of ANN models used for the estimation of pollutant emission into the atmosphere (Alonso et al. 2007; Antanasijević et al. 2013, 2014; Khoshnevisan et al. 2013; Stamenković et al. 2016). Thus, ANNs, using pressure indicators as inputs, were successfully applied for GHG prediction purposes in Serbia by Radojević et al. (2013) and Antanasijević et al. (2014) applied ANNs for forecasting of GHG emissions of European countries, using broadly available sustainability, economical, and industrial indicators as inputs. Also, Stamenković et al. (2016) developed an artificial neural network model for the prediction of annual NMVOC emissions, using economical and sustainability indicators as inputs. The trend of GHG emissions in Japan was analyzed using ANNs, based on forecasted electricity consumption (Huang and Nagasaka 2012). Furthermore, ANNs were successfully applied for CO_2 prediction in Iran, using primary energy consumption as network input (Yousefi et al. 2013). Similar research was performed in China, where ANNs were used for providing a more reliable estimate of CO_2 emissions based on industrial consumption of three kinds of primary energy (Liu 2013). However, none of the studies addressed ANNs as a vital tool in planning and developing energy policy for any particular country, thus leaving actual benefits of implementing artificial intelligence in society unexplored.

Croatia is a new member of European Union and recently has become subjected to significant changes of its legislative. This brought many new factors to be considered, especially in a field of environmental protection that was requiring inevitable changes of current policies. Croatian-specific combination of political, economical, and geospatial characteristics presents specific challenge when talking about reduction of GHG missions. This work focuses on potential benefits of implementation of artificial neural networks as a tool for modeling of policies for reduction of GHG emissions. The case study of Croatia is addressed, and the ANN prediction model based on energy consumption per sector is developed. The model is used to define a more efficient and environmentally more sustainable mitigation policy which incorporates all climate and energy directives of EU and UNFCCC. In principle, the proposed model should be transferable to other parties by applying the described ANN training procedure using appropriate data.

Greenhouse gas emissions

As a member of EU, Croatia took an obligation to reduce GHG emissions for 20 and 40% by 2020 and 2030, respectively, as compared to year 1990 (European Commission 2014).

As an Annex I Party of UNFCCC, Croatia has the obligation of monitoring and reporting its annual GHG inventory covering emissions and removals of direct GHGs (carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3)) originating from five greenhouse gas emission sectors (termed energy; industrial processes and product use; agriculture, forestry, and other land use; waste; and other), and for all years from the base year (or period) to 2 years before the inventory is due (UNFCCC Conference 2013).

The main greenhouse gas emission sectors, along with definitions of activities and greenhouse gases, included are presented in Table 1 (IPCC Guidelines 2006).

Regarding Croatia, the energy sector is the most important of the sectors contributing to climate change and mentioned in the Intergovernmental Panel on Climate Change (IPCC). The energy sector includes all GHG emissions arising from fuel combustion and fugitive releases of fuels which are sum of all

Table 1 Classification and definition of categories of emissions and removals

Category code and name	Definition	Gases
1. Energy	This category includes all GHG emissions arising from combustion and fugitive releases of fuels. Emissions from the nonenergy uses of fuels are generally not included here but reported under industrial processes and product use sector.	CO_2, CH_4, N_2O, NO_x, CO, NMVOC, SO_2
2. Industrial processes and product use	Emissions from industrial processes and product use, excluding those related to energy combustion (reported under 1A), extraction, processing and transport of fuels (reported under 1B) and CO_2 transport, injection, and storage (reported under 1C)	CO_2, CH_4, N_2O, HFCs, PFCs, SF_6, other halogenated gases, NO_x, CO, NMVOC, SO_2
3. Agriculture, forestry, and other land use	Emissions and removals from forest land, cropland, grassland, wetlands, settlements, and other land. Also includes emissions from livestock and manure management, emissions from managed soils, and emissions from liming and urea application. Methods to estimate annual harvested wood product (HWP) variables are also covered in this category.	CH_4, N_2O, CO_2
4. Waste		CO_2, CH_4, N_2O, NO_x, CO, NMVOC, SO_2
5. Other		N_2O

the categories and subcategories from 1A, 1B, and 1C, as described in 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC Guidelines 2006).

The energy sector in Croatia accounted for approximately 75% of the total national GHG emissions, with CO_2 as the largest individual anthropogenic contributor. In 2013, the GHG emissions from the energy sector were lower than emissions in 1990 by 27.2%. The total GHG emissions in 2013, excluding removal by sinks, amounted to 24.493 million tons CO_2 eq, which represents the reduction with respect to 1990 by 30.3%. Although GHG emissions did not change significantly during the entire period from 1990 to 2013 (Figs. 1 and 2), a certain decrease was observed in the first years of Homeland war (1990–1992) for obvious reasons. After 1992, a slight but permanent increase of GHG emissions was occurring, which ended by the economic crisis in 2008. The observed general downward trend in GHG emissions in the period 2008–2013 was not only the result of a decline in economic activity but also a consequence of implementation of energy efficiency measures and increased use of renewable energy sources (Energy Institute Hrvoje Požar 2014).

Similar to CO_2 emission, the emissions of NO_x, CO, NMVOC, and SO_2 also decreased with regard to 1990 levels. Figure 2 shows the emissions of ozone precursors in the period 1990–2013. The emission of NO_x from energy sector in 2013 was 51.3 Gg which was 36% lower compared to 1990; NO_x emissions from energy sector contributed with 95% to total NO_x emission. In the energy sector, the main sources of NO_x emission in 2013 were subcategories transport, energy industries and manufacturing industries, and construction (Croatian NIR 2015). The emission of CO from energy sector in 2013 was 129.7 Gg which was 62.9% lower than in 1990; the ratio of CO emissions from energy sector in total CO emission for 2013 was 90%. The largest contributors of CO emissions in 2013 were subcategories transport and some elements from the subcategory other sectors (residential and commercial/institutional) (Croatian NIR 2015). Nonmethane volatile organic (NMVOC) emissions from energy sector in 2013 were 17.8 Gg and were 58.7% lower than in 1990; NMVOC emissions from energy sector took 33% of total NMVOC emission. The main sources of NMVOC emission in energy sector were mainly from other sectors subcategory (residential and commercial/institutional), which accounted for 54.7% (Croatian NIR 2015). In 2013, energy sector had SO_2 emission of 13.3 Gg which was 90.4% lower compared to 1990. The SO_2 emission had the overall decreasing trend due to consumption of fossil fuels with lower sulfur content. The largest contributors of SO_2 emissions in 2013 were from fuel combustion activities category (Croatian NIR 2015).

In order to achieve decarbonization of the economy, between 2005 and 2014, Croatia has decreased its GHG emissions by 14%. According to its 2015 projections, Croatia is expected to reach its 2020 target with a 20% margin as compared to 2005 (European Commission 2015). In addition, Croatia has not established yet a medium to long-term climate and energy strategy for the post 2020 period. The Energy Development Strategy (EDS) includes both energy and climate-related objectives and covers the period up to 2020 (European Commission 2015). The new Energy Development Strategy which will be based on comprehensive Low Carbon Development Strategy until 2030 with the view to 2050 and beyond has not been adopted yet.

Sectoral energy consumption

Final energy consumption covers all energy supplied to the final consumer for all energy uses. It is usually disaggregated

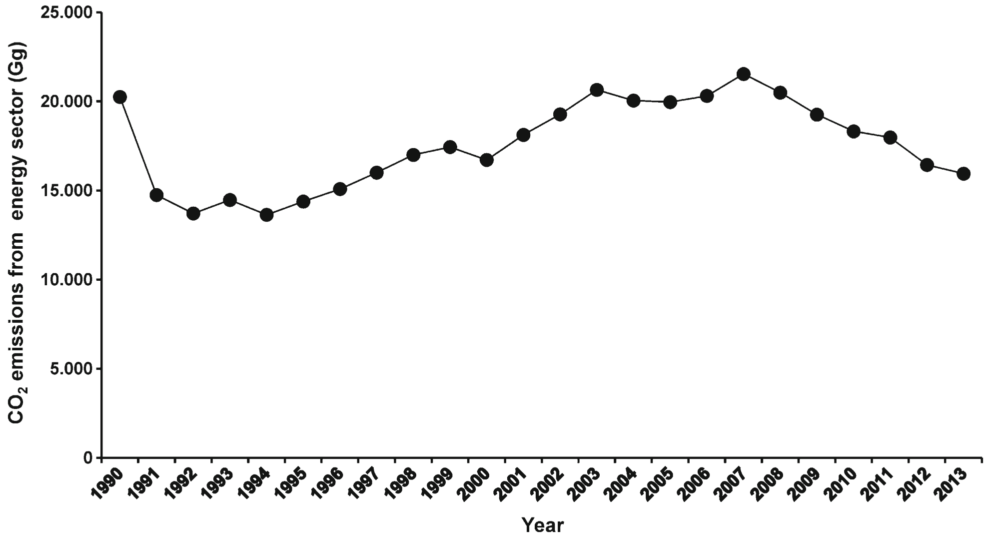

Fig. 1 CO_2 (*circles*) emissions from energy sector (data source: Croatian NIR 2015)

into the end-use sectors (consumption sectors): industry, transport, households, services, agriculture, and construction (European Environment Agency 2009).

Due to the war-time destruction in mid-1990s, Croatia's industry was devastated and the overall energy consumption, especially in the industry sector, experienced a substantial decline. All the other sectors (transport, households, services, agriculture, and construction) generally began to recover after the war and the energy demand started to increase again, see Fig. 3. As a result of this, the total final energy consumption reached the pre-war levels by 2010 (Pukšec et al. 2013). However, the industry sector, as a most important consumption sector with respect to national economy, never recovered. It reached the peak energy consumption as early as 1994. After the war end in 1995, the energy consumption in industry sector practically remained constant until 2008 when it experienced another distinct contraction caused by the global economic crisis and wide recession. After the war, the households sector took over the highest share in energy consumption for the next 11 years. During that period, the transport sector indicated stable growth in energy consumption, and it took over the top position in 2006. Despite the negative effects of the recession, it withheld its leading position till 2012. Although the negative economic trends caused by recession in 2008 still continue, at least modest economic growth in the next few years is expected. Accordingly, final energy consumption should show a similar pattern.

Final energy consumption according to the type of energy used is divided in six categories: coal and coke, liquid fuels, gaseous fuels, renewable energy sources, electricity, steam, and hot water (Energy Institute

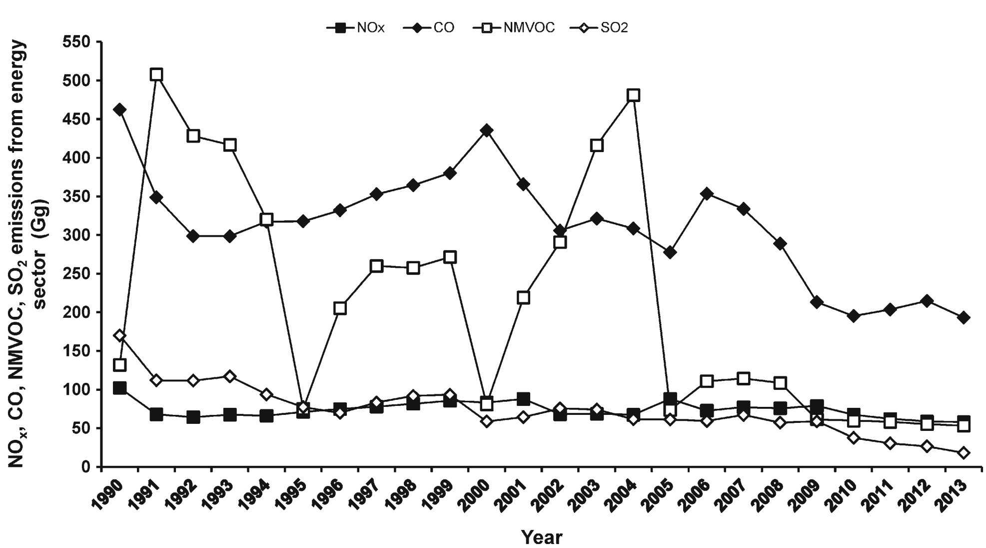

Fig. 2 NO_x (*filled squares*), CO (*filled diamonds*), NMVOC (*empty squares*), and SO_2 (*empty diamonds*) emissions from energy sector (data source: Croatian NIR 2015)

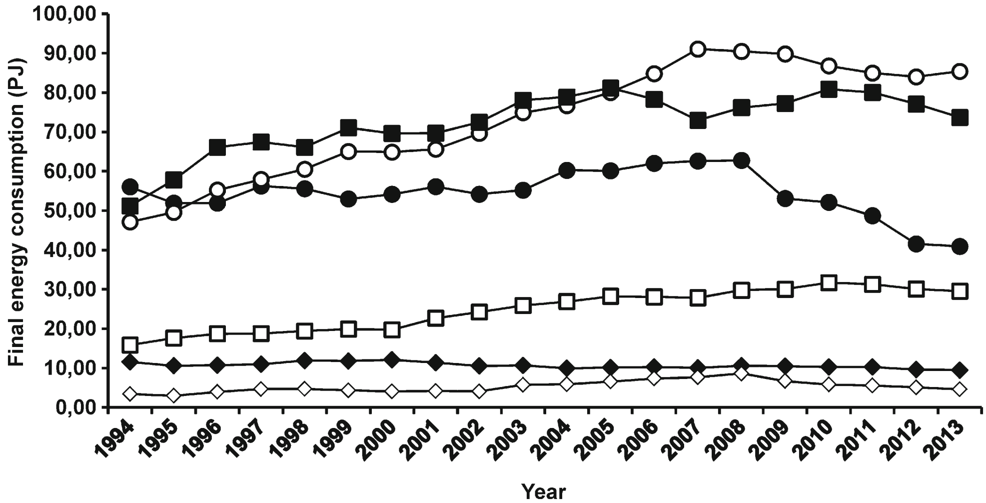

Fig. 3 Final energy consumption by industry (*filled circles*), transport (*empty circles*), households (*filled squares*), services (*empty squares*), agriculture (*filled diamonds*), and construction (*empty diamonds*) sector in Croatia from 1994 till 2013 (data source Energy Institute Hrvoje Požar 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Hrvoje Požar 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014). The consumption in Croatia is dominated by liquid fuels, followed by electricity, gaseous fuels, renewable energy sources, and steam and hot water, see Fig. 4.

Croatia's 2020 energy efficiency target is set up to 11.5 Mtoe expressed in primary energy consumption which is 7.0 Mtoe expressed in final energy consumption which is 293.07 PJ (European Commission 2015).

Business as usual and sustainable scenarios

At the end of 2009, Croatia has adopted the Energy Development Strategy (EDS of Croatian Parliament 2009). EDS is still the only valid strategic document in Croatia. The new document considering the low-carbon strategy is in drafting process; in its development, hopefully the methodology presented in this article will be used. Therein, the two scenarios of energy consumption were presented: business as usual (BAU) and sustainable scenario. Energy consumption per sector was projected up to 2020 and 2030, respectively, by using analogy methods (by comparing the Republic of Croatia to EU15 countries) and other econometric methods (Croatian Ministry of Economy and UNDP 2008). In the BAU scenario, the final energy consumption was based on an assumption that the consumption growth is purely determined by market trends and consumer's habits, without governmental intervention and without implementation of new advanced technologies. On the

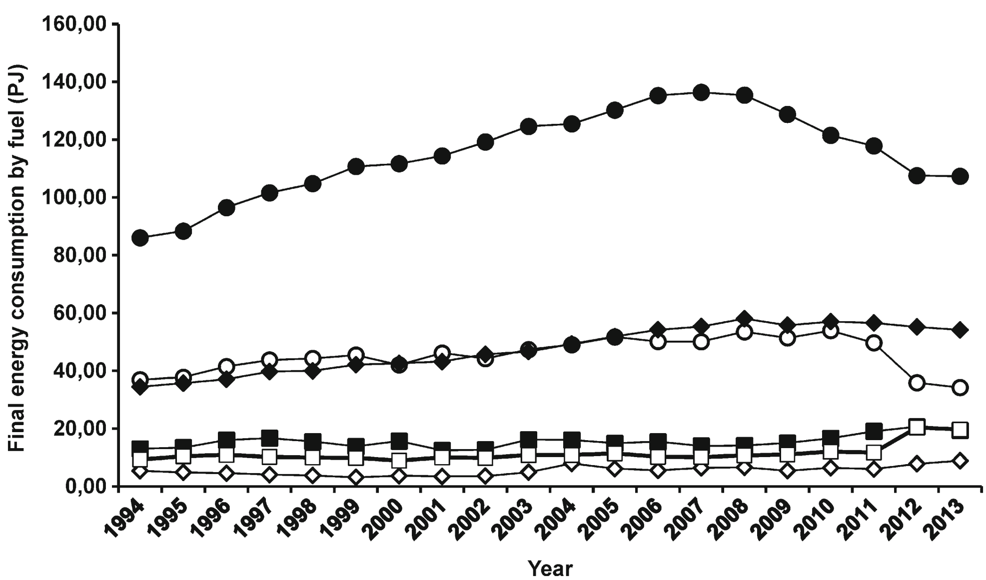

Fig. 4 Final energy consumption in Croatia according to different fuels in period 1994–2013. The classes presented are coal and coke (*empty diamonds*), liquid fuels (*filled circles*), gaseous fuels (*empty circles*), renewable energy sources (*filled squares*), electricity (*filled diamonds*), steam and hot water (*empty squares*) (data source Energy Institute Hrvoje Požar 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

contrary, the sustainable scenario is used to achieve goals of EDS. It is a result of energy policy measures proposed in EDS. The proposed mitigation measures to reduce GHG emissions in sustainable scenario can be divided into two main groups. The first group, when applied, would have direct effects on decreasing the energy losses and could be termed simply as

- Reduction of final energy consumption through energy efficiency measures, (G1).

The second group of proposed mitigation measures would have direct effects on reducing the GHG emissions and could be evaluated under three distinctive topics, as follows:

- Increasing the use of renewable energy sources (G2A).
- Using the best available techniques for preventing the greenhouse gas emissions (G2B).
- Applying the EU Emissions Trading System (EU ETS) (G2C).

According to the projections from EDS, the final energy consumption in BAU grows at an average annual rate of 3.1% per year from 267.89 PJ (2006) to 409.60 PJ (2020) and 500.84 PJ in 2030. After the application of energy efficiency measures in the sustainable scenario, the final energy consumption grows at an average annual rate of 2.7% per year from 267.89 PJ (2006) to 386.84 PJ (2020) and 470.60 PJ in 2030. Average annual growth rates vary by consumption sector, with transport sector having the highest rate at 3.3%, followed by the growth rate for sectors households, services, agriculture, and construction (termed others in the original document) set to the equal value of 3.1% and by the industry sector having the lowest growth rate of 2.6% (EDS of Croatian Parliament 2009). The average share in final energy consumption of industry sector is 21% and in transport sector is 32.5%, and in other sectors category, average share in final energy consumption is 46.5%.

After evaluation of the recent events due to the economic crisis and consequently after reducing energy consumption with respect to years mentioned in EDS, the actual energy consumption and the average annual growth rate for sectors were taken into account in order to get more realistic values of energy consumption in upcoming years, in particular for the years 2020 and 2030, respectively. The average final energy consumption growth rates used in this paper in order to calculate final energy consumption were based on growth rates listed in EDS. The growth rates from EDS were adjusted, i.e., for both scenarios in order to obtain more realistic values according to the current economic situation.

Artificial neural networks

ANN topology

The neural network used in this paper was the three-layer feedforward neural network. The input layer consisted of six neurons representing annual energy consumption per each of the six sectors (industry, transport, households, services, agriculture, and construction) in the period 1994–2013. The input experimental data were scaled to the mean value of 0 and standard deviation of 1. This was found necessary because, although most neural networks can accept input values in any range, they had proved to be sensitive to inputs in a far smaller range. Output layer consisted of five neurons representing emissions of five different GHGs (CO_2, NO_x, CO, NMVOC, and SO_2) in the same period, which were compared to the available data. The training algorithm and number of neurons in hidden layer and the number of experimental data points used for training calculations need to be optimized. Therefore, training algorithm was varied between gradient descent algorithm with adaptive learning rate (*GDA*), gradient descent with momentum and adaptive learning rule (*GDX*), Powel–Beale conjugate gradient (*CGB*), quasi-Newton algorithm with Broyden, Fletcher, Goldfarb, and Shanno update (*BFG*), Levenberg–Marquardt (*LM*), and Levenberg–Marquardt algorithm with Bayesian regularization (*BR*). The number of neurons in hidden layer was varied from 2 to 30.

To test the predictive performance of the developed artificial neural network model, an independent validation set for the years 2012 to 2015 was used followed by extensive statistical evaluation. The validation set was chosen in accordance with the final use of ANN, i.e., the exploration in the forward (future) time series. All the calculations were performed in MATLAB R2016a (MathWorks, Sherborn, USA) environment.

ANN training

The simplest implementation of training ANN is based on adaptation of the network weights and biases in the direction in which the performance function decreases most rapidly, i.e., the negative of the gradient. The $(k + 1)$th iteration of this algorithm, as described in Demuth and Beale (2004), can be written as

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha_k \mathbf{g}_k \tag{1}$$

where $\mathbf{x}_k$ is the vector of current weights and biases, $\mathbf{g}_k$ is the current gradient, and α_k is the learning rate. The gradient descent algorithm with adaptive learning rate is based on a heuristic technique (Vogl et al. 1988); it is much faster than the standard steepest descent algorithm as it allows for the learning rate to change during the training process. This procedure increases the learning rate; however, the rate is limited by the requirement that there is no large increase of the error.

In the conjugate gradient algorithms, the search is performed along conjugate directions, which produces generally faster convergence than for the steepest descent direction case. All the conjugate gradient algorithms start by searching in the steepest descent direction on the first iteration (Eq. (2)). Then, a line search is performed to determine the optimal distance to move along the current search direction (Eq. (3)):

$$\mathbf{p}_0 = -\mathbf{g}_0 \tag{2}$$

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k \tag{3}$$

The next search direction is determined so that it is conjugate to previous search directions:

$$\mathbf{p}_k = -\mathbf{g}_k + \beta_k \mathbf{p}_{k-1}. \tag{4}$$

The variants of conjugate gradient are distinguished by the manner in which the constant β_k is computed. The Powell–Beale update procedure for computation is characterized by two features: (a) the search direction is reset to the negative of gradient if there is very little remaining orthogonality between the current gradient and the previous gradient, which is tested by the inequality (Eq. (5)), and (b) the search direction is computed by Eq. (4) where parameter β_k can be computed in several different ways.

$$\left|\mathbf{g}_{k-1}^{\mathrm{T}}\mathbf{g}_k\right| \geq 0.2\|\mathbf{g}_k\|^2 \tag{5}$$

Newton's method, as described in Chong Edwin and Zak Stanislaw (2004) and Demuth and Beale (2004), is an alternative to the conjugate gradient methods for fast optimization. The basic step of Newton's method is

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{A}_k^{-1}\mathbf{g}_k \tag{6}$$

where $\mathbf{A}_k$ is the Hessian matrix (second derivatives) of the performance index at the current values of the weights and biases. It is complex and expensive to compute the Hessian matrix for feedforward neural networks. Therefore, a quasi-Newton method is used for this purpose, which updates an approximate Hessian matrix at each iteration of the algorithm. The update is computed as a function of the gradient by using the following Eq. (7), as illustrated in Chong Edwin and Zak Stanislaw (2004).

$$\mathbf{A}_{k+1} = \mathbf{A}_k + \left(1 + \frac{\Delta\mathbf{g}_k^{\mathrm{T}}\mathbf{A}_k\Delta\mathbf{g}_k}{\Delta\mathbf{g}_k^{\mathrm{T}}}\right)\frac{\Delta\mathbf{x}_k\Delta\mathbf{x}_k^{\mathrm{T}}}{\Delta\mathbf{x}_k^{\mathrm{T}}\Delta\mathbf{g}_k} - \frac{\mathbf{A}_k\Delta\mathbf{g}_k\Delta\mathbf{x}_k^{\mathrm{T}} + \left(\mathbf{A}_k\Delta\mathbf{g}_k\Delta\mathbf{x}_k^{\mathrm{T}}\right)^{\mathrm{T}}}{\Delta\mathbf{g}_k^{\mathrm{T}}\Delta\mathbf{x}_k} \tag{7}$$

The Levenberg–Marquardt training algorithm (Hagan and Menhaj 1994) is designed to achieve second-order training rate without computing the Hessian matrix. When the performance function has the form of a sum of squares (as usually is the case in training feedforward networks), then the Hessian matrix can be approximated by Eq. (8) and gradient can be computed by Eq. (9) where $\mathbf{J}$ is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases and $\mathbf{e}$ is a vector of network errors.

$$\mathbf{H} = \mathbf{J}^{\mathrm{T}}\mathbf{J} \tag{8}$$

$$\mathbf{g} = \mathbf{J}^{\mathrm{T}}\mathbf{e} \tag{9}$$

The Levenberg–Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \left[\mathbf{J}^{\mathrm{T}}\mathbf{J} + \mu\mathbf{I}\right]^{-1}\mathbf{J}^{\mathrm{T}}\mathbf{e} \tag{10}$$

It is a well-known fact that larger networks can create overly complex functions and smaller networks are susceptible to overfitting the data. Those problems can be redressed by employing the Bayesian regularization method through weight decay (Demuth and Beale 2004). The performance function, which is typically mean sum of squares (MSE), of the network errors, e

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} e^2 \tag{11}$$

can be modified by adding a penalty term that consists of the mean of the sum of squares of the network weights and biases, x

$$\mathrm{MSW} = \frac{1}{n}\sum_{i=1}^{n} x^2 \tag{12}$$

to create the regularized mean sum of squares function

$$\mathrm{MSE}_{\mathrm{REG}} = \gamma\mathrm{MSE} + (1-\gamma)\mathrm{MSW} \tag{13}$$

where γ is the performance ratio of regularization parameter and n is the number of network parameters. Using $\mathrm{MSE}_{\mathrm{REG}}$, performance function causes the network to attain smaller weights and biases, which smoothes the network response and makes it less likely to overfit.

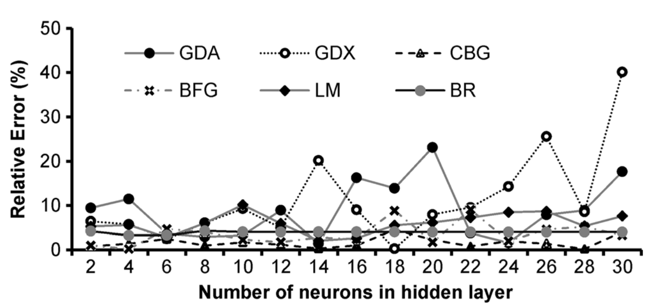

Fig. 5 ANN GHG model optimization for CO_2

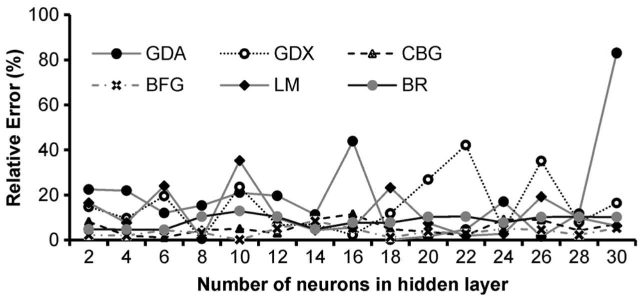

Fig. 6 ANN GHG model optimization for NO_x

Finding optimum network architecture for prediction of GHG emissions

Figures 5, 6, 7, 8, and 9 illustrate the procedure for finding optimum ANN architecture for prediction of GHG emissions. It can be seen that training algorithms which use first-order information often get stuck in local minima indicating the instability of the training process. This can be proved by the fact that *GDA* algorithm exhibit very deep minima of relative error for every particular GHG emission (1.90% on average), but at the different number of neurons in hidden layer for different GHGs (20 for CO_2, 18 for NO_x, 26 for CO, 8 for NMVOC, and 16 for SO_2). At the same time, the average of relative error for GDA over all GHGs and across the whole investigated range of number of neurons in hidden layer (2 to 30) was as high as 15.36%. Moreover, validation was performed in all cases on the set of three consecutive years only. All these facts may suggest that the overfitting was very likely to occur. (Validation with a larger data set would probably result with a higher error as a consequence of the reduction of training data set.) The same conclusion can be withdrawn for GDX algorithm which is also based on first-order information. However, implementation of variable learning rate indeed contributed to some improvement, and local minima observed were somewhat shallower (values were not lower than 2.27% in the extreme case). On the contrary, CGB, BFG, and LM training are based on second-order information and the observed average values of relative errors over all GHGs and across the whole investigated range of number of neurons in hidden layer (2 to 30) were 11.45, 11.05, and 10.21%, respectively. The second-order information brought

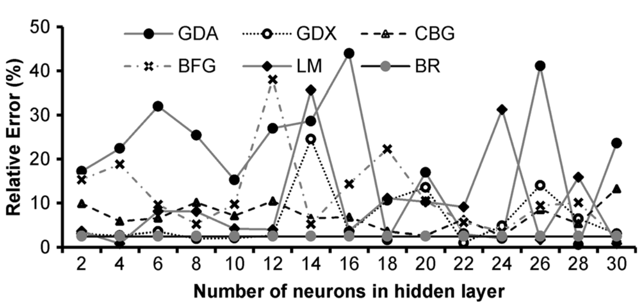

Fig. 7 ANN GHG model optimization for CO

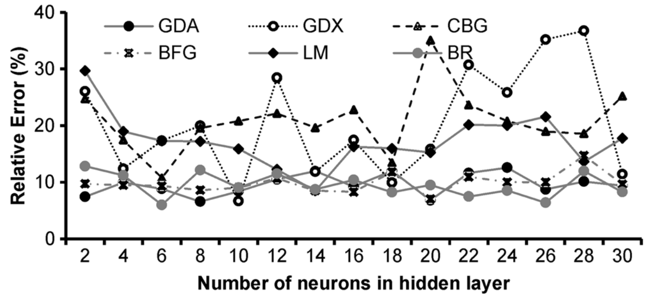

Fig. 8 ANN GHG model optimization for NMVOC

about much more stability in the training process, but the inconsistency with respect to finding the optimum number of neurons in hidden layer neurons still remained. By introducing regularization in the estimation of error (Eq. (13)), the training process became extremely stable (this is particularly important for subsequent extrapolation). This can be proved, e.g., by the fact that the smallest relative error of GHG emission prediction was found for six neurons in hidden layer for all the investigated GHGs. The summary of validation results is presented in Fig. 10. All subsequent calculations were therefore performed using *LM–BR* training methodology and six neurons in hidden layer.

Application of ANN model

As mentioned before, the final use of ANN was the exploration in the forward (future) time series of GHG emissions. Future values of energy consumption by sector data, needed as inputs for ANN, were obtained by applying the extrapolation over the data at hand (1994 to 2015), using the average annual growth rate as extracted from EDS, for two different scenarios. The BAU scenario used the 2.7% average annual growth rate starting from 265.05 PJ (2016) to 294.69 PJ (2020) and 384.29 PJ in 2030, respectively. The growth rate was lowered to original 3.1% from EDS due to the economic crisis in a somewhat arbitrary manner since no actual date was available for the comparison, i.e., the mitigation measures were already active. The applied average annual growth rate varied between sectors with transport sector showing the highest growth rate of 2.9% followed by the other sectors category (households, services, agriculture, and construction)

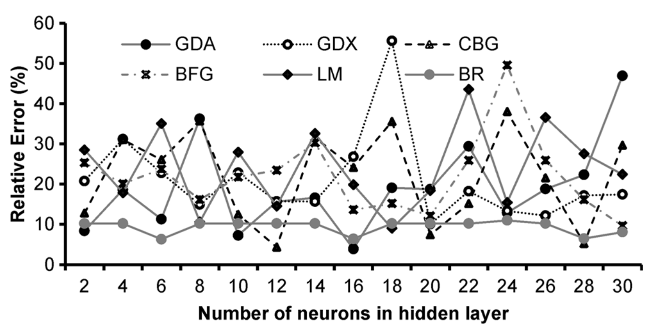

Fig. 9 ANN GHG model optimization for SO_2

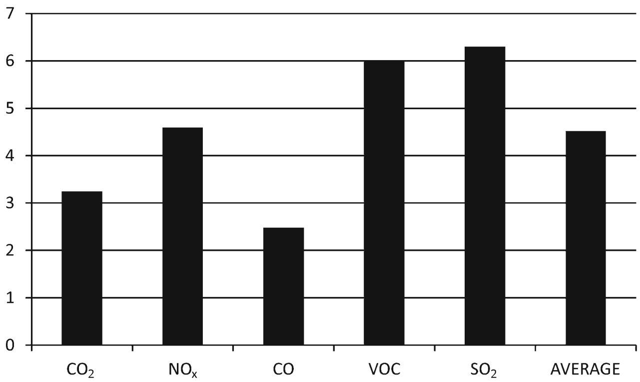

Fig. 10 Summary of validation results of ANN GHG model optimization, percent error for every particular GHG, and average over all GHGs

set to 2.7% and industry sector with the lowest growth rate of 2.2%. Energy consumption data per sector according to BAU scenario are presented in Tables 2 and 3.

The application of energy efficiency measures as proposed in EDS would eventually lead to the so-called sustainable scenario, with diminished and hopefully more realistic values of average annual growth rate of energy consumption per sector. Under assumption that the share of every sector in the period 2016–2030 will approximately stay the same as it is now, with the assumed increase in GDP and with applied energy efficiency measures, the reduction in final energy consumption of 20% in the sustainable scenario was forecasted with respect to BAU. The reasoning was as follows. In 2013, the revised projections of final energy consumption in Croatia were adopted in the National Action Plan for Renewable Energy Sources to 2020 (Ministry of Economy 2013). Therein, the economic recovery and consequently the increase in final energy consumption has been predicted for 2013 with a growth rates for all economic sectors 1.8% for the whole period to 2020. In reality, this did not happen with a decrease of GDP of −1.1% in 2013, and the crisis continued in 2014 with −0.5% decrease of GDP. The recovery began only in 2015 with 1.6%, and in 2016, the rate of 2.9% increase of GDP was observed (Croatian National Bank 2017). The rate of 3.5% was assumed for 2017 and 2018, 4.0% for 2019 and 2020, 4.5% for period 2021–2027, and 4.4% for 2028–2030.

By assuming the elasticity of the increase of final energy consumption and the GDP amounting to 0.61 for 2015, 0.56 for 2016–2022, and 0.47 for 2023–2030, the average annual growth rate of final energy consumption of 2.1% was calculated which corresponds to 20% lowering with respect to (already lowered) value for BAU scenario (2.7%).

Therefore, in the sustainable scenario, the average annual growth rate of 2.1% was used and a consumption starting from 261.44 PJ (2016) to 285.41 PJ (2020) and 355.49 PJ in 2030, respectively. Within this scenario, the transport sector and the other sectors category (households, services, agriculture, and construction) had the growth rate of 2.3% per annum, followed by the industry sector with the growth rate of 1.8% annually. The calculated energy consumption data per sector according to sustainable scenario are presented in Tables 4 and 5.

Having the inputs defined, ANN model was applied to predict GHG emissions for both energy consumption scenarios (BAU and sustainable scenario).

Prediction results for GHG emissions for BAU scenario are obtained as depicted in Fig. 11. The figure shows that in the given period (2013–2030), CO_2 emissions will slowly continue to rise from 19,438 Gg in 2013 up to 20,843 Gg in 2020 and eventually in 2030 will go further up to 21,994 Gg, which is an increase of 2500 Gg. The emissions of ozone precursors show more rapid growth. NO_x emissions will rise from around 25 Gg in 2013 up to 31.14 Gg in 2020 and up to 46.59 Gg in 2030, which is almost more than twice of the emissions in 2013. CO emissions will grow from 292.98 Gg in 2013 up to 321.57 Gg in 2020 and 392.75 Gg in 2030. NMVOC emissions will grow from 77.63 Gg in 2013 up to 112.37 Gg in 2020 and 237.56 Gg in 2030, which is around three times more than it was in 2013. SO_2 emissions will also grow from 27.25 Gg in 2013 up to 45.41 Gg in 2020 and 74.23 Gg in 2030, which is also around three times more than it was in 2013. The results clearly illustrate the need for urgent action in this field.

The prediction results for sustainable scenario (after applying mitigation measures as given in (Ministry of Economy 2014), which are primarily reflected through lower final energy consumption), show lower values of GHG emissions for all investigated gases as depicted in Fig. 12. The figure shows

Table 2 Prediction of energy consumption according to business as usual scenario 2016–2023

Average annual rate 2012–2020	Energy sector	2016	2017	2018	2019	2020	2021	2022	2023
2.2	Industry	43.88	44.84	45.83	46.84	47.87	48.92	50.00	51.10
2.9	Transport	90.54	93.16	95.86	98.64	101.50	104.45	107.48	110.59
2.7	Households	83.74	86.00	88.32	90.70	93.15	95.67	98.25	100.90
2.7	Services	28.09	28.84	29.62	30.42	31.24	32.09	32.95	33.84
2.7	Agriculture	12.67	13.01	13.36	13.73	14.10	14.48	14.87	15.27
2.7	Construction	6.14	6.31	6.48	6.65	6.83	7.01	7.20	7.40
Total final energy consumption (PJ)		265.05	272.16	279.47	286.98	294.69	302.61	310.75	319.10

Table 3 Prediction of energy consumption according to business as usual scenario 2024–2030

Average annual rate 2021–2030	Energy sector	2024	2025	2026	2027	2028	2029	2030
2.2	Industry	52.22	53.37	54.54	55.74	56.97	58.22	59.50
2.9	Transport	113.80	117.10	120.50	123.99	127.59	131.29	135.10
2.7	Households	103.63	106.43	109.30	112.25	115.28	118.39	121.59
2.7	Services	34.76	35.70	36.66	37.65	38.67	39.71	40.78
2.7	Agriculture	15.68	16.10	16.54	16.99	17.44	17.92	18.40
2.7	Construction	7.60	7.80	8.01	8.23	8.45	8.68	8.92
Total final energy consumption (PJ)		327.69	336.50	345.55	354.85	364.40	374.21	384.29

Table 4 Prediction of energy consumption according to sustainable scenario 2016–2023

Average annual rate 2012–2020	Energy sector	2016	2017	2018	2019	2020	2021	2022	2023
1.8	Industry	43.36	44.14	44.94	45.75	46.57	47.41	48.26	49.13
2.3	Transport	88.96	91.01	93.10	95.24	97.43	99.67	101.97	104.31
2.3	Households	82.76	84.66	86.61	88.60	90.64	92.73	94.86	97.04
2.3	Services	27.76	28.40	29.05	29.72	30.40	31.10	31.82	32.55
2.3	Agriculture	12.52	12.81	13.11	13.41	13.72	14.03	14.35	14.68
2.3	Construction	6.07	6.21	6.35	6.50	6.65	6.80	6.96	7.12
Total final energy consumption (PJ)		261.44	267.23	273.16	279.22	285.41	291.74	298.22	304.83

that in the given period (2013–2030), CO_2 emissions will slowly continue to rise from 19,438 Gg in 2013 up to 20,662 Gg in 2020 and eventually in 2030 will go further up to 21,102 Gg. The emissions of ozone precursors show similar growth as it is depicted in predictions in BAU scenario. NO_x emissions will rise from around 25 Gg in 2013 up to 29.27 Gg in 2020 and up to 42.77 Gg in 2030. CO emissions will grow from 292.98 Gg in 2013 up to 314.62 Gg in 2020 and 378.45 Gg in 2030. NMVOC emissions will grow from 77.63 Gg in 2013 up to 102.48 Gg in 2020 and 221.16 Gg in 2030. SO_2 emissions will also grow from 27.25 Gg in 2013 up to 42.12 Gg in 2020 and 70.61 Gg in 2030.

The sum of all five greenhouse gas emissions in this paper in 2015 were 20,480 Gg; in 2020 21,151 Gg; in 2025 21,478 Gg; and in 2030 21,815 Gg. Those results represent only emissions from energy sector which is approximately 75% of total greenhouse gas emissions in Croatia.

For comparison, the Report on Projections of Greenhouse Gas Emissions—Annex 2015 (Croatian Environment Agency, 2015) gives historical emissions and projections of

Table 5 Prediction of energy consumption according to sustainable scenario 2024–2030

Average annual rate 2021–2030	Energy sector	2024	2025	2026	2027	2028	2029	2030
1.8	Industry	50.01	50.91	51.83	52.76	53.71	54.68	55.67
2.3	Transport	106.71	109.17	111.68	114.25	116.87	119.56	122.31
2.3	Households	99.27	101.56	103.89	106.28	108.73	111.23	113.79
2.3	Services	33.30	34.06	34.85	35.65	36.47	37.31	38.17
2.3	Agriculture	15.02	15.37	15.72	16.08	16.45	16.83	17.22
2.3	Construction	7.28	7.45	7.62	7.79	7.97	8.16	8.34
Total final energy consumption (PJ)		311.60	318.52	325.59	332.82	340.21	347.76	355.49

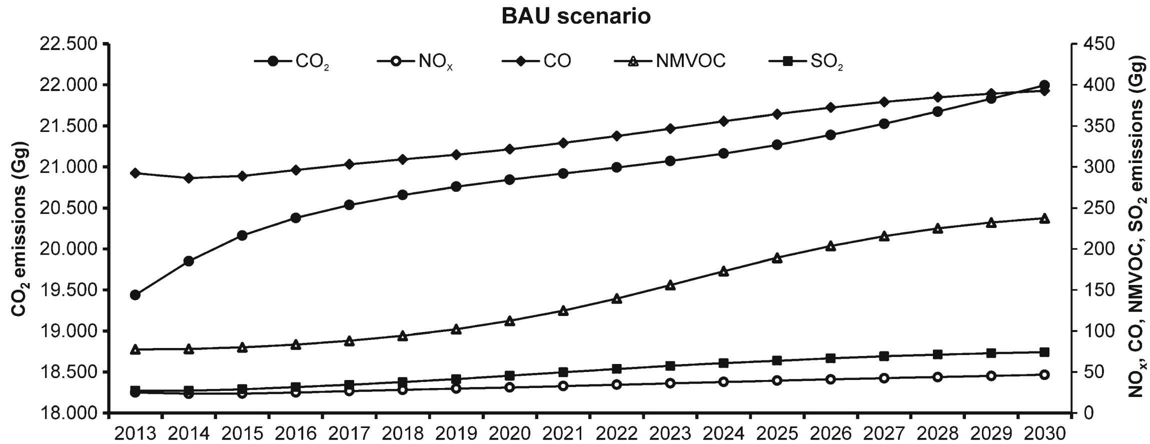

Fig. 11 Predicted greenhouse gas emissions for business as usual (BAU) scenario

total greenhouse gas emissions in energy sector along with three different scenarios elaborated therein. For example, the worst scenario (no mitigation measures at all) gives 14.523, 18.769, 20.205, and 21.811 Gg CO_2 eq in 2015, 2020, 2025, and 2030, respectively. The values for other two scenarios are significantly lower. The approach presented here gives similar figures; however, for the case with energy efficiency (G1), measures applied. Therefore, one has to conclude that—if calculations presented here are assumed correct—there is a mismatch between the EDS of Croatian Parliament (2009) and the Report (Croatian NIR 2015).

To get true insight, it is more interesting to compare the decrease of emissions with respect to BAU scenario than to consider the absolute values of emissions, see Fig. 13. The figure indicates that planned mitigation measures for CO_2 emissions would not produce the desired result, at least not immediately. Even having the measures introduced at this very moment, the significant decrease of CO_2 emissions with respect to BAU would not be observed until 2023 and the maximum decrease in 2030 would amount not more than 4%. The measurable effect on reduction of NO_x and NMVOC emissions (10 and 20% with regard to BAU, respectively) would be sensed much earlier, with a maximum reached around 2024. The reduction of CO emissions would reach its maximum of 5% with respect to BAU in 2026 with subsequent slow decline. The applied mitigation measures would firstly affect SO_2 emissions; the maximum decrease with respect to BAU would be found as early as 2021. In conclusion, Fig. 13 shows that for each gas investigated (greenhouse gases and ozone precursors), it takes different time for the proposed emission reduction measures to show effects.

Sustainable scenario was found capable of producing the decrease in GHG emissions with respect to BAU; however, the increase with respect to current values is predicted. This might indicate that mitigation measures are not effective enough in order to reach the desired goal of lowering GHG emissions. Nevertheless, it has to be taken into account that the applied ANN can predict only the reduction of GHG emissions that originates from G1, i.e., from the reduction of final energy consumption through energy efficiency measures. Thus, the application of ANN helped us to separate the effect of two main groups of mitigation measures in EDS. Lowering of GHG emissions through G2A, G2B, or G2C could not be evaluated since the original database used in creation of ANN did not contain information relevant to those groups.

Conclusion

The purpose of this paper was the development of a reliable tool which could be used for testing various policies for GHG emission reduction. To achieve this, only GHG emissions from fuel combustion activities in energy sector as outputs were correlated with the historical data for final energy consumption per all six (consumption, end-use) sectors (industry, transport, households, services, agriculture, and construction) as inputs. A three-layer feedforward ANN was used for the correlation. It was shown that the optimum ANN architecture

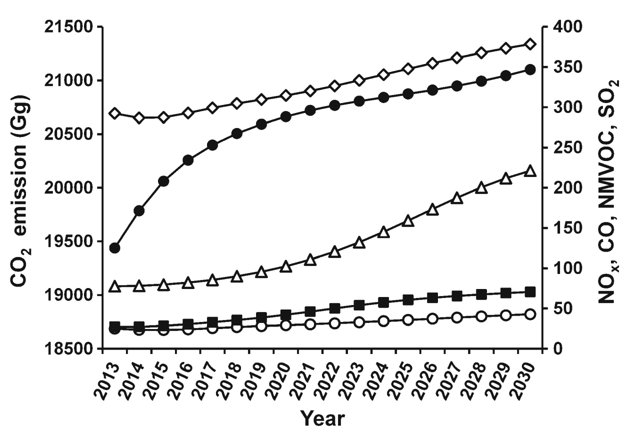

Fig. 12 Predicted greenhouse gas emissions for sustainable scenario

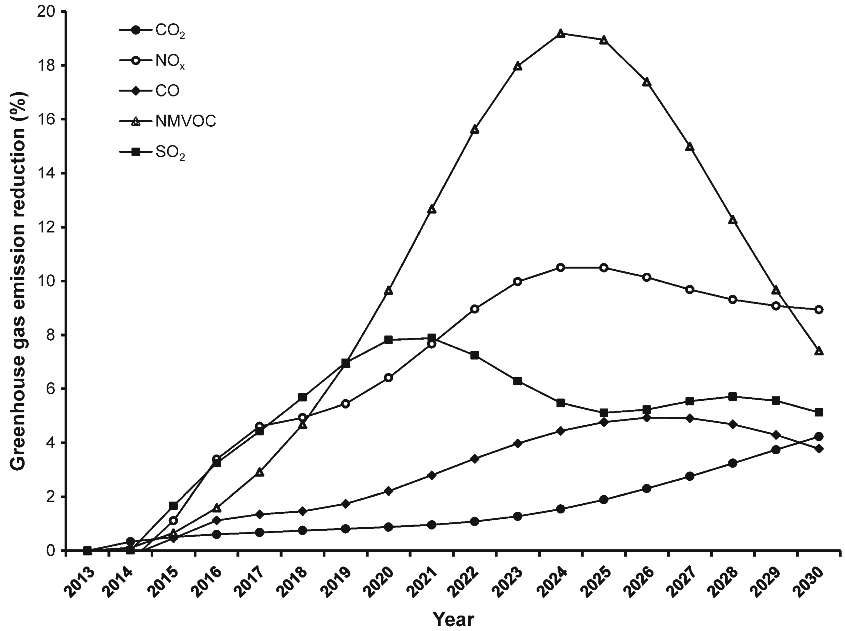

Fig. 13 Predicted reduction of GHG emissions for sustainable scenario with respect to BAU scenario

consisted of six neurons in hidden layer and that the Levenberg–Marquardt algorithm with Bayesian regularization incorporated provided the best training performance. The resulting network exhibited reliable prediction of GHG emissions. The network was used to evaluate the two energy consumption scenarios adopted in the Energy Development Strategy of Croatia. When comparing them, the sustainable scenario was found to produce the decrease of GHG emissions with respect to BAU, as expected. However, only the part of the decrease originating from the reduction of final energy consumption through energy efficiency measures (G1) is predicted. Thus, it was possible to separate the effect of the mitigation measures into two parts, which would surely help policy makers to produce right decisions in the future.

ANN, artificial neural network; BAU, business as usual; BFG, quasi-Newton algorithm with Broyden, Fletcher, Goldfarb, and Shanno update; BR, Levenberg–Marquardt algorithm with Bayesian regularization; CERA, Croatian Energy Regulatory Agency; CGB, Powel–Beale conjugate gradient; EDS, Energy Development Strategy (of Croatian Parliament); ETS, Emissions Trading System; EU, European Union; GDA, gradient descent algorithm (with adaptive learning rate); GDX, gradient descent (X—with momentum and adaptive learning rule); GHG, greenhouse gases; IPCC, Intergovernmental Panel on Climate Change; LM, Levenberg–Marquardt algorithm; MSE, mean sum of squares of the network errors; MSE_{REG}, mean sum of squares of the network errors with Bayesian regularization included; MSW, mean sum of squares of the network weights and biases; NMVOC, nonmethane volatile organic compounds; UNDP, United Nations Development Program; UNFCCC, United Nation Framework Convention on Climate Change

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Compliance with ethical standards

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