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Emission Allowances Prices Predictions for the Purposes of Managerial Decision Making

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Abstract: This study is focused on predictions of emission allowances prices within the EU ETS for the purposes of managerial decision making; precisely the study presents possibilities of the EUA auction price development forecasts with application of so called unconventional managerial decision-making methods as linguistic and fuzzy models. Firstly, the study presents the background of the EU emissions trading system and an overview of different methods used in current research connected with CO_2 emission allowances. The key task of the study is an application of one selected model of the fuzzy models group to emission allowances price development predictions. In this consequence, the study presents comparison of prediction results obtained from LFLF and ARIMA models. The prediction errors, advantages and disadvantages of LFLF are discussed; furthermore, the practical usage of emission allowances price predictions in decision making process is suggested. LFLF model can be valuable tool for predictions of the EUA price development since the errors are similar as regarding ARIMA model; however, LFLF is able to predict more precisely the shape of the price development curve.

Key words: Emission allowances trading, EUA price, fuzzy modelling, prediction, LFLF model

INTRODUCTION

The EU emissions trading system: Generally, the emission allowances trading, also known as cap and trade, belongs to the family of the economic tools of negative externalities internalization for particular emissions cutting (Besides trading with emissions (mainly CO_2, NO_x, SO_2), we can find also tradable fish quota or trading in waste sector, water protection sector and land protection sector (Jilkova, 2003; EEA, 2006; Kolstad, 2011)). National or sub-national emission trading systems are already operating in Australia, the European Union, Japan, New Zealand, Switzerland and the United States and are planned in Canada, China and South Korea (European Commission, 2013). The suitable example is US Sulphur Allowance System also called as an Acid Rain Program (More detail for example in Kolstad (2011)). Market history and experience from this Program suggest that once emissions cap and trade programs are established, there is long term, relatively stable emissions allowance market performance with gradually declining prices as significant emission reductions are achieved.

The European Union also established a scheme for emission allowances trading, the EU emissions trading system also called EU ETS, dealing with greenhouse gas emissions. The scheme is substantially larger and by far more complex than the pioneering US sulphur allowance system (Conrad *et al*., 2012). The initial EU emissions trading system was based on directive 2003/87/EC which established a fundamentally decentralized system for the pilot phase of emissions trading (2005-2007) and the Kyoto Protocol commitment phase (2008-2012). The key instrument here was the preparation of National Allocation Plans (NAPs) (Wettestad *et al*., 2012). Currently, based on directive 2009/29/EC, the EU ETS has step into Phase III (2013-2020), the post-Kyoto commitment period.

The EU ETS is actually the largest emissions market in the world; however in comparison with energy markets it is relatively small (Conrad *et al*., 2012). The EU ETS covers >11,000 power stations and manufacturing plants in the 28 EU member states as well as Iceland, Liechtenstein and Norway. Aviation operators flying within and between most of these countries are also covered. In total, around 45% of total EU emissions are limited by the EU ETS (European Commission, 2013).

A sufficiently high carbon price promotes investment in clean, low-carbon technologies. The regulatory framework of the EU ETS was largely unchanged for the first two trading periods of its operation, however the beginning of the third trading period in 2013 brings changes in common rules (Published as Directive

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2009/29/EC) which should strengthen the system. Since, the EU emission allowances were previously grandfathered (Grandfathering = For free) from year 2013 the most important yield of the emission allowances will be auctioned. Grandfathering was widely criticized, mostly because it introduced significant distortions to the EU emissions trading system (Falbo *et al.*, 2013). Auctioning is the most transparent method of allocating allowances and puts into practice the polluter pays principle (European Commission, 2013). NAPs were abolished; an EU-wide ETS emission cap was introduced and national allocations were to be derived from this common cap. Sectorial differentiation was introduced with (initially) far more auctioning of allowances for energy producers than energy-intensive industries. In addition, free allocations were further harmonized, to be based on common state-of-the-art technology benchmarks (Wettestad *et al.*, 2012).

Regarding all changes in common rules in the third trading period, it is obvious that the cap on CO_2 emissions from power stations and other fixed installations should be reduced by 1.74% every year. This means that in 2020, greenhouse gas emissions from these sectors will be 21% lower than in 2005 (A separate cap applies to the aviation sector: for the whole 2013-2020 trading period, this is 5% below the average annual level of emissions in the years 2004-2006) (European Commission, 2013). We can say that policy makers give firms an incentive to move towards production that is less fossil-fuel intensive (Aatola *et al.*, 2013).

In last years, CO_2 became a significant member of the European commodity trading market. However, there is a fundamental difference between trading in CO_2 and more traditional commodities. Sellers are expected to produce fewer emissions than they are allowed to, so they may sell the unused allowances to someone who emits more than the allocated amount. Therefore, the emissions become either an asset or a liability for the obligation to deliver allowances to cover those emissions (Benz and Truck, 2009). The market price of the allowances is determined by supply and demand. Both in the first and in the second trading period, the EU emission allowances were traded mostly on the BlueNext trading exchange (BlueNext, 2012). In 2012, 7.9 billion allowances were traded with a total value of 56 billion (European Commission, 2013). In the third trading period, there has only been one big exchange which can be used for emission rights trading European Energy Exchange (EEX).

Overview of CO_2 emission allowances studies: Since, an emission allowances trading have started in the USA, the majority of publications dealing with price of tradable emission allowances assess the market for SO_2 emissions under the Acid Rain Program. Regarding the EU ETS, scientists have focused mostly on modelling and forecasting the prices of CO_2 emission allowances (Benz and Truck, 2009; Nahorski and Horabik, 2010; Li *et al.*, 2011; Conrad *et al.*, 2012; Garcia-Martos *et al.*, 2013; Lecuyer and Quirion, 2013). The researchers of scientific papers have used various methods for their research, Table 1 shows an overview of methodologies and research objects of examined studies.

It is essential for carbon market players and their managerial decision making to learn about CO_2 price dynamics in order to realize trading strategies, risk strategies and investment decisions. Benz and Truck (2009) categorize the principle driving factors of CO_2 allowance prices into: policy and regulatory issues and market fundamentals that directly concern the production of CO_2 and thus demand and supply of CO_2 allowances. Policy and regulatory issues have mostly a long-term impact on prices, on the other hand the consequences of changes in such regulatory or policy issues may be sudden price jumps, spikes or phases of extreme volatility in allowance prices.

We have focused our research both on emission allowances trading as a tool for CO_2 emission reduction and fuzzy modelling. Fuzzy modelling is a suitable tool for predictions in case of high volatility and uncertainty. Generally, time series analysis and prediction is an important task that can be used in many areas of practice. The task of getting the best prediction to the given series may bring interesting engineering applications in a wide number of areas as economics, geography or industry (Dvooak *et al.*, 2003). After detailed research of scientific papers, dealing simultaneously with fuzzy modelling and emission trading, we observed that fuzzy modelling was used for modelling grazing rights (McCarthy and Goodhue, 1999) and modelling emission trading rules for asymmetric emission uncertainty estimates (Nahorski and Horabik, 2010; Li *et al.*, 2011). However, there is a lack of scientific studies trying to predict the EUA price or the traded volume of emission allowances using the instruments of fuzzy modelling.

Based on these findings, this study applies one of the fuzzy modelling methods to predictions in the emission allowances trading area in the EU. The key task of the paper is an application of one selected model of the fuzzy models group to emission allowances price development predictions, comparison of prediction results obtained from the selected Fuzzy Model with results obtained from ARIMA Model and finally discussion of prediction errors, advantages and disadvantages of both

Table 1: Overview of CO_2 emission allowances studies

Researchers (years)	Methodologies	Object of research
Lund (2007)	Micro-economic valuation	Primary cost effects from EU ETS effect on the price of purchased electricity and the direct CO_2 emission reduction cost
Chernyavs´ka and Gulli (2008)	Load duration curve approach and the dominant firm with competitive fringe model	Impact of CO_2 price on power pricing when electricity markets are imperfectly competitive
Benz and Truck (2009)	Regime-switching models GARCH Models (GARCH = models of non-constant volatility) ARCH models (ARCH = Auto Regressive Conditional Heteroscedasticity; heteroscedasticity = non-constant variance)	Spot price modelling and forecasting
Nahorski and Horabik (2010)	Fuzzy modelling - grounding the derivations in the fuzzy set approach	Modelling the uncertainty of greenhouse gases emission inventories
Grainger and Kolstad (2010)	Consumer Expenditure Survey and an input-output model	Modelling the incidence of a price on carbon induced by a cap-and-trade program or carbon tax in the context of the US
Li *et al*. (2011)	Fuzzy Modelling an interval-fuzzy two-stage stochastic programming model	Planning CO_2 emission trading in industry systems under uncertainty
Conrad *et al*. (2012)	GARCH Models	Modeling the adjustment process of EUA´s (EUA = 1 EU emission allowance) prices to scheduled macroeconomic and regulatory announcements
Aatola *et al*. (2013)	An equilibrium model of the emissions trading market	Price determination in the EU ETS market
Falbo *et al*. (2013)	Model based on the profit function	The impact of EUAs on the optimal policy of a competitive electricity producer
Garcia-Martos et al. (2013)	ARIMA Models (ARIMA = Auto Regressive Integrated Moving Average models) VARIMA Models (VARIMA = Vector ARIMA Models multivariate time series models)	Building a multivariate model for the aforementioned prices and comparing its results with those of univariate ones
Lecuyer and Quirion (2013)	Analytical and numerical model of the EU energy and carbon markets	Implications of the possibility of a nil carbon price on optimal policy instrument choice
Lutz *et al*. (2013)	Markov regime-switching GARCH model	Examination of the nonlinear relationship between the EUA price and its fundamentals

Researchers

of selected models; furthermore the practical usage of emission allowances price predictions in decision making process in companies and public economics is suggested.

MATERIALS AND METHODS

Dealing with the EU emission allowances markets, there are available data regarding auctions, spot and futures. For the purposes of the predictions presented in this article, the daily closing prices of the EUA, auction market 13-20 (EEX, 2014) are used. Figure 1 shows the development of the EUA auction price in period 11/2012 7/2014. The auction's days are Monday, Tuesday and Thursday every week.

General overview: Our current research is focused on complete analysis of the EU ETS and its possible impacts, consequences and influence (Zimmermannova and Eermak, 2014). The applied methodology is based on testing of various tools connected with fuzzy modelling. Generally, fuzzy modelling is a method of describing the behaviour of real systems using fuzzy logic and fuzzy reasoning (Germak, 2005). Several tapes of fuzzy models have been developed and used in various fields of applications.

For the purposes of the EUA auction price predictions, we have used 2 different models which can be considered as conventional and unconventional models LFLF (Linguistic Fuzzy Logic Forecaster) and ARIMA (Auto Regressive Integrated Moving Average). The first model, LFLF, represents the unconventional models group and it is based on fuzzy modelling, the second model, ARIMA, represents a statistical analysis model that uses time series data to predict future trends. We have used the above mentioned models for the EUA auction price prediction for the next 12 auctions days.

Linguistic Fuzzy Logic Forecaster (LFLF): LFLF (Linguistic Fuzzy Logic Forecaster) is a specialized tool for an analysis and forecasting time series (This tool was originally developed by the Institute for Research and Applications of Fuzzy Modelling (IRAFM), University of Ostrava, Czech Republic; the software program LFLF is available here: http://irafm.osu.cz/en/c110_lfl-forecaster). It is based on various methods, the first method is the fuzzy transform, the second one is the linguistic description (fuzzy IF-THEN rules) and the third one is the perception-based logical deduction.

The fuzzy transform: The core idea of the fuzzy transform (F-transform) technique is a fuzzy partition of the universe. It can be simply presented as a set of intervals fulfilling some criteria. It is described in the following definition (Perfilieva *et al.*, 2008): let $x_1<, ..., <x_n$ be fixed

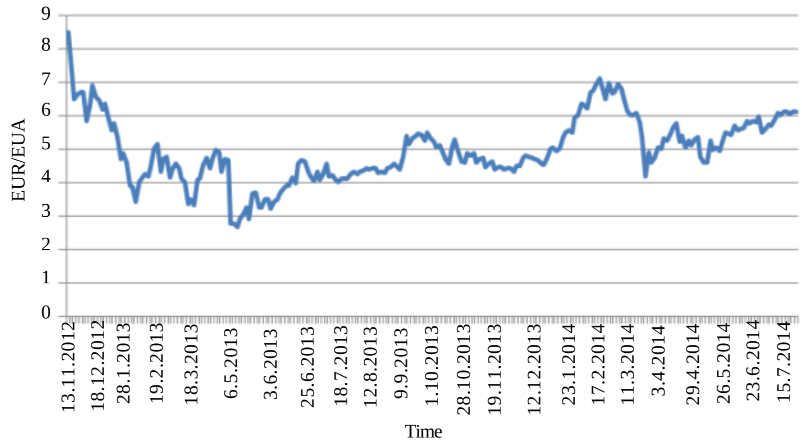

Fig. 1: Development of the EUA auction price 2012-2014; EEX (2014)

nodes within [a, b] such that $x_1 = a$, $x_n = b$ and n = 2. We say that fuzzy sets $A_1,...,A_n$ identified with their membership functions $A_1(x),...,A_n(x)$ defined on [a, b] form a fuzzy partition of [a, b] if they fulfil the following conditions for k = 1,..., n:

- A_k: [a, b]→[0, 1], $A_k(x_k) = 1$
- $A_k(x) = 0$ if $x \notin (x_{k-1}, x_{k+1})$ where for the uniformity of denotation, we put $x_0 = a$ and $x_{n+1} = b$
- $A_k(x)$ is continuous
- $A_k(x)$, k = 2, ..., n, monotonically increases on $[x_{k-1}, x_k]$ and $A_k(x)$, k = 1, ..., n-1, monotonically decreases on $[x_k, x_{k+1}]$
- For all x∈[a, b]

$$\sum_{k=1}^{n} A_k(x) = 1$$

The membership functions $A_1(x),...,A_n(x)$ are called basic functions. These partitions form a base for F-transform which leads to the tuple of numbers representing the original transformed function. The n-tuple can be obtained using the following notion. Let $f \in V_l$ be given and $A_1,...,A_n$, $n<l$, be basic functions which constitute a fuzzy partition of [a, b]. We say that the n-tuple of real numbers $[F_1, ..., F_n]$ is the F-transform of f with respect to $A_1,...,A_n$ if:

$$F_k = \frac{\sum_{j=1}^{l} f(p_j) A_k(p_j)}{\sum_{j=1}^{l} A_k(p_j)}, \quad k = 1,...,n$$

The numbers $F_1,...,F_n$ are called the components of the fuzzy transform of f. Let $F_n[f]$ be the fuzzy transform of f with respect to $A_1,...,A_n$. Then, the function $f_{F,n}$ given on [a, b] by:

$$f_{Fn}(x) = \sum_{k=1}^{n} FkA_k(x)$$

is called the inverse fuzzy transform of f. To forecast time series, its F-transform representation is used and separately forecast the next component Y_{n+1} of the F-transform (y_t) and a respective residuum is forecast. Three methods for the forecasting components of the F-transform are considered: the F-transform of the second order, an extrapolation of the inverse fuzzy transform and a logical deduction (Dvooak *et al*., 2003).

The linguistic description (fuzzy IF-THEN rules): The theory of linguistic term and variables enables to work with the rules containing the terms of natural language as small or big and modifiers, e.g., very, roughly, etc. The rule interpretation is then done by logical deduction based on the fuzzy set theory and fuzzy logic to enable deducing conclusions on the basis of imprecise description of the given situation using the linguistically formulated fuzzy IF-THEN rules. The usage of this theory within a frame of time series prediction lies in the learning of these rules from the series and then their application to the future (predicted) members of the series (Dvooak *et al*., 2003). Fuzzy IF-THEN rules can be understood as a specific conditional sentence of natural language of the form:

IF X_1 is A_1 AND,...,AND X_n is A_n THEN Y is B

Where, $A_1,...,A_n$ and B are evaluative expressions (very small, roughly big, etc.).

The perception-based logical deduction: Perception-based Logical Deduction (PbLD) is a special method of deducing conclusions on the basis of a linguistic description. This method can be described as follows: if a linguistic description consisting of fuzzy IF-THEN rules together with an observation of some value of the variable X are given than the PbLD chooses the most specific fuzzy rules among the most fired ones and derives a conclusion based on such preselected fuzzy rules (Novak and Perfilieva, 2004; Novak *et al.*, 2010).

ARIMA: Auto Regressive Integrated Moving Average (ARIMA) (This tool is a part of software program STATGRAPHICS Centurion XVI and is available here: http://www.statgraphics.com/statgraphics_centurion.htm) models processes are a class of stochastic processes used to model and forecast time series. The model is shortly described in this paper, since it has been used and sufficiently described in many studies (for example, Garcia-Martos *et al.*, 2013).

Let $p_{j,t}$ be the price of the jth series under study. Usually, time series of prices are log transformed to remove the most evident type of heteroskedasticity and then, once the variance has been stabilized, a regular difference is applied to the log-prices in order to get stationarity in mean. By doing so, the observed series becomes stationary both in variance and mean. Let $y_{j,t} = \log(p_{j,t})-\log(p_{j,t-1})$ be the return series of the prices $p_{j,t}$. Then, the dependence structure of the stationary series in variance and mean, $y_{j,t}$ can be modelled by an ARMA(p,q) Model whose general expression is given by:

$$\Phi(B)ey_{j,t} = \theta(B)a_t, a_t \sim \mathrm{NIID}(0,\sigma_2^a)$$
$$(1-\varphi_1 B-\varphi_2 B^2-\ldots-\varphi_p B^p)ey_{j,t} =$$
$$(1-\theta_1 B-\theta_2 B^2-\ldots-\theta_p B^p)\, a_{j,t}$$

Where:

$ey_{j,t}$ = $y_{j,t}$-$y_{j,t}$

B = The lag operator such that $By_{j,t} = y_{j,t-1}$

The error term a_t is assumed to be Normally, Independent and Identically Distributed (NIID). The model described by equation for $ey_{j,t}$ can be written as follows for the original series of prices $y_{j,t}$:

$$\varphi(B)\nabla(\log(p_{j,t})) = \theta(B)a_t,\ a_t \sim \mathrm{NIID}\,(0, \sigma_2^a)$$

Where the difference operator ∇ = 1-B. If $y_{j,t}$ is generated by and ARMA(p,q) Model and only one difference was needed to stabilize the mean, then the log $(p_{j,t})$ is generated by an ARIMA (p, d = 1, q) Model where d is the order of integration.

Prediction errors: For the purposes of this study, we have focused on the following errors: MAE (the Mean Absolute Error), MSE (the Mean Squared Error) and MAPE (the Mean Absolute Percentage Error). The Mean Absolute Error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The Mean Squared Error (MSE) measures the average of the squares of the errors. The Mean Absolute Percentage Error (MAPE) expresses accuracy as a percentage.

RESULTS

As was mentioned in study, the following research is based on the data set originally published by EEX which describes the beginning of the third trading period of the EU ETS. For the purposes of our research, we have selected one part of the time series. It is period 11/2012 9/2013, since the real EUA auction price curve had interesting shape in October 2013. In October 2013, the real EUA auction price curve looks like letter W. Therefore, we would like to try to use both of the models for this price curve shape prediction.

At first, we must prove the analysed time series for ARIMA Model through autocorrelations of residuals. Figure 2 shows the results for ARIMA Model (2,0,1), you can see that this model is not absolutely adequate; however other BJ-Models have no better results. So, we will continue with Model ARIMA(2,0,1) for the next steps of our prediction.

Figure 3 shows the comparison of results of predictions obtained from LFLF and ARIMA models. LFLF results consist of LFLF Forecast and LFLF Trend; ARIMA results consist of ARIMA Lower 95% limit, ARIMA Upper 95% limit and ARIMA forecast. Besides the forecast, you can see also the real EUA auction price data ("Reality" in Fig. 3), published by EEX. It is apparent that predictions of both of the Models LFLF and ARIMA are near the real data from EEX; however both of the forecasted data curves have milder shape than the real market EUA auction price curve.

Figure 4 shows the EUA auction price forecast in detail, consisting of LFLF, ARIMA and Reality curves. It is apparent that both of the predicted EUA auction price time series fluctuate between 4,9 EUR/EUA and 5,3 EUR/EUA. On the other hand, you can see that despite the fact that the real EUA auction price curve has the shape of letter W, the predictions are a little different. LFLF forecast is closer to the reality in the first 8 trading days and at the end of the forecasted period, the LFLF curve has similar progress as the Reality curve; however in the other days of the prediction you can see the different shape of LFLF and reality curves. On the other hand, you can see that ARIMA model can predict the whole trend of the EUA auction price development; LFLF model can predict more precisely the shape of the EUA auction price curve.

Now, we should focus on forecasting errors. Firstly, we can compare the forecasted values of the EUA auction prices with the real EUA auction prices data published by EEX. Figure 3 and 4 show the comparison of particular values predicted by LFLF and ARIMA (2,0,1) with the corresponding real values in graphical expression.

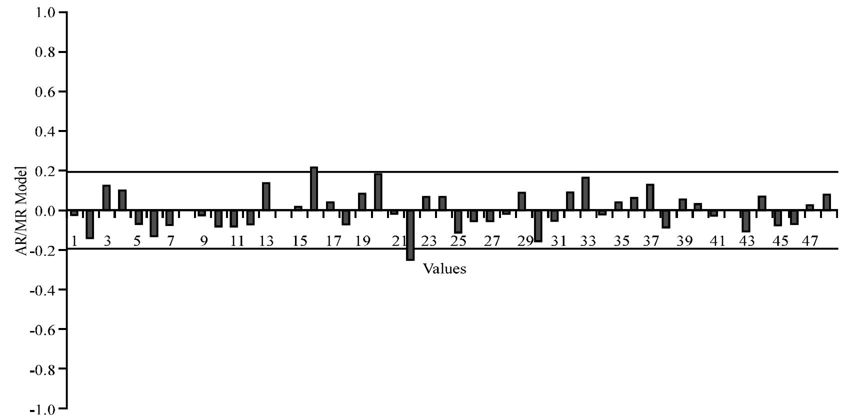

Fig. 2: Autocorrelations of residuals; researchers

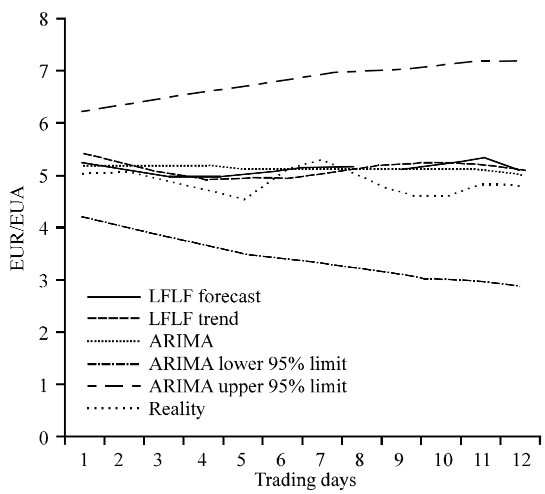

Fig. 3: The EUA auction price forecast comparison

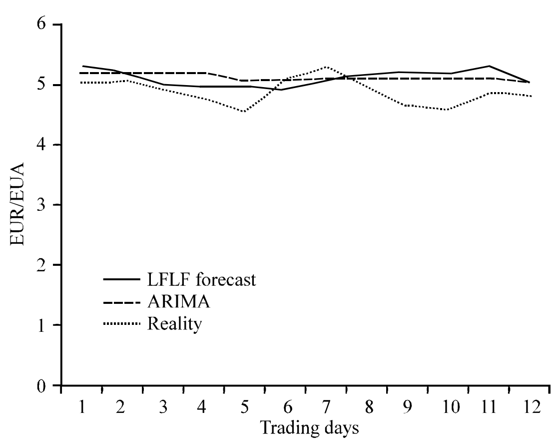

Fig. 4: The EUA auction price forecasts in detail

However, we can verify the results of the models with the help of the following indicators: MAE (the mean absolute error), MSE (the mean squared error) and MAPE (the mean absolute percentage error). Table 2 shows the results of our verification.

Table 2: Prediction errors-comparison of LFLF and ARIMA

	LFLF			ARIMA		
Time	MAE	MSE	MAPE	MAE	MSE	MAPE
1	0,265195	0,070328	0,052514	0,15	0,0225	0,029703
1-2	0,171077	0,038125	0,033802	0,125	0,01625	0,024655
1-3	0,154621	0,030355	0,030848	0,19	0,044967	0,038295
1-4	0,17885	0,038584	0,036516	0,2675	0,096225	0,055317
1-5	0,229092	0,067857	0,048158	0,326	0,1397	0,068923
1-6	0,217812	0,06089	0,045438	0,276667	0,116567	0,058422
1-7	0,20912	0,055711	0,043202	0,261429	0,104043	0,054684
1-8	0,211692	0,055342	0,043614	0,24875	0,094237	0,051897
1-9	0,24745	0,080819	0,051543	0,272222	0,107278	0,057146
1-10	0,284973	0,11151	0,059985	0,297	0,12359	0,062785
1-11	0,300276	0,120053	0,063028	0,292727	0,118036	0,061764
1-12	0,29697	0,115709	0,062319	0,286667	0,112233	0,060452

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It is obvious that the presented errors are not high. The Mean Absolute Percentage Error (MAPE) value for 12 predicted values is 6, 23% (LFLF) and 6, 04% (ARIMA). Table 2 shows the lowest errors highlighted in the MAPE column. For the purposes of this article, MAPE has been counted from aggregate values specified in the "Time" column. Regarding LFLF, we can see the lowest errors for the prediction of the EUA auction price in the first 10 trading days. Generally, the prediction of the shorter time period is more accurate, for example the Mean Absolute Percentage Error (MAPE) value for the first 8 predicted values is only 4.36%.

DISCUSSION

Generally, focusing on CO_2 emissions regulation and trading within the EU ETS, it should be mentioned that there are different opinions of particular economists and politicians regarding emission trading system as a whole and its efficiency (Regarding efficiency and real impacts of particular economic instruments of environmental policy you can Pavel *et al*., 2009 or Zimmermannova and Mensik, 2013), reasonability and real impacts on economy, energy sector, transportation and environment. For example Nordhaus (2005, 2011) compared emission allowances with CO_2 taxation and strongly recommended environmental taxes. On the other hand, Wettestad *et al*. (2012) strengthened the argument that new rules under Directive 2009/29/EC can lead to more effective and better organized emission trading system. The most cited negative aspect of emission allowances (both carbon dioxide and sulphur dioxide) is the volatility (Regarding volatility you can see for example Mareek (2014) in the market price of carbon under the emissions-targeting approach (The prices of US SO_2 emission allowances has been almost three times as volatile as stocks and more than half as volatile as oil. The volatility of CO_2 allowances in the EU emission trading system is similarly large (Nordhaus, 2011)). The volatility arises because of the inelasticity of both supply and demand for emission allowances (Nordhaus, 2005, 2011). The more stable and predictable market price of 1 tonne of CO_2 is important, since the public institutions and companies can calculate with CO_2 market price in preparation of both energy and environmental policy design and particular investment strategies. The market price of CO_2 emission allowances can affect managerial decision making, for example the emission allowances prices and their predictability can affect the design of future electricity generation mix (Rentizelas *et al*., 2012). The emission allowances price can be also expected to reflect the cost of reducing the next incremental ton of emissions (EPA, 2009).

Many factors can affect the emission allowances price including fuel markets, weather, technology availability and performance (Lutz *et al*., 2013; Aatola *et al*., 2013). When there are real or perceived changes in market fundamentals that impact this cost, there are subsequent adjustments in allowance prices. These adjustments can stem from market forces including the price of coal and natural gas, the demand for electricity related to weather and other factors and the availability and reliability of technology. They can also stem from regulatory forces which can impact the overall supply and demand of the market (EPA, 2009). Moreover, the EU ETS is structurally linked to the global climate regime, through the possibility for EU companies to use credits from the Kyoto Protocol's flexibility mechanisms (Clean Development Mechanism and Joint Implementation) for compliance purposes in the EU ETS. Although, this possibility enhances the cost-effectiveness of the system, it also introduces uncertainty about a possible "flooding of the ETS" by external credits that place downward pressure on the carbon price (Wettestad *et al*., 2012).

As you can see in the previous chapter "Results", it is obvious that the EUA auction price can be forecasted; however the key task for the economists is the suitable forecasting model selection. We have observed and compared the results from one conventional and one unconventional model, LFLF and ARIMA and we can say that both of the models can be used for predictions in the EUA auction price area. Since, the added value of this article is mainly LFLF Model application for the EUA auction price predictions, we should evaluate both advantages and disadvantages of this selected model. Generally, we can say that the model needs huge volume of data (at least 90 figures); on the other hand the availability of data does not automatically mean reliable results of a forecast. Suitable results rely on both availability of data and presence of trend components in particular time series. Since, the prices of emission allowances are both uncertain and volatile, LFLF can be valuable tool for predictions the EUA auction price (Nordhaus, 2011; Lutz *et al*., 2013).

Comparing LFLF and ARIMA, we can see similar prediction errors and similar trend; on the other hand the EUA auction price prediction curve shape forecasted by LFLF is more precise in the first eight days (based on both graphical expression of prediction and MAPE). For the purposes of short-time predictions, LFLF can be better than ARIMA.

Based on the above mentioned results and comments, LFLF can serve as a supportive instrument for managerial decision making in particular companies and public institutions in the area of emission reductions, environmental investments (Pawliczek and Piszczur, 2013) brought interesting results regarding sustainable development priorities of entrepreneurs, the most focused priorities of investments) and both environmental and energy policy. Expecting the future investments of companies, the prediction can provide management with the additional information; thereby the economists and managers of particular companies can plan the most suitable timing of particular investments. As is said by Aatola *et al*. (2013), information on market price development is important to all market participants besides compliance traders you can find there also speculators who use price information to manage and hedge their portfolios.

On the other hand, the LFLF can provide suitable additional data also to public sector management. As is mentioned by EPA (2009), the price of an allowance in a cap and trade program can be expected to reflect the marginal cost of compliance or the cost of reducing the next incremental ton of emissions. It can be very valuable for public sector and its managerial decision making, since the public administrative have poor awareness of current costs of companies. We can also discuss the EU emission allowances price development and its possible consequences for CO_2 related taxes setting and modification as one part of the managerial decision process in public economics. Comparing the actual EUA auction price with CO_2 taxation proposed by EU Commission, it is obvious that the proposed CO_2 tax rates are approximately 3-times higher than the real EUA auction price on the primary emission allowances market in December 2014 (EUA auction price 16.12.2014-6,93 EUR (EEX, 2014) versus proposal of CO_2 tax - 20 EUR/1 ton of CO_2).

CONCLUSION

This study presents the background of the EU ETS, overview of current scientific studies dealing with the CO_2 emission allowances price and its methods and finally the comparison of the EUA auction price predictions based on conventional and unconventional methods, precisely results of predictions obtained from ARIMA and LFLF forecasting models. The results of particular predictions are also compared with the real market data from EEX and the significant errors are analysed.

It is obvious that availability of data does not automatically mean reliable results of a forecast; on the other hand LFLF forecaster can be valuable tool for predictions of the EUA auction price development since the errors are similar as regarding ARIMA Model; however LFLF is able to predict more precisely the shape of the price development curve.

Based on the above mentioned research, we can conclude that the EUA auction price predicted with the help of fuzzy modelling, represented in this study by LFLF forecaster can serve as an additional source of information for managerial decision making both for the private and public authorities; however the better predictability of the EUA auction prices can also help to accelerate the innovation impact of the EU ETS.

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