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Predicting Trends in Cereal Production in the Czech Republic by Means of Neural Networks

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Abstract

This paper deals with problems of processing agricultural production data into the form of time series and analysing consequent results by means of two completely different methods. The first method for calculating cereals production figures uses the MS-Excel spreadsheet using conventional mathematical and statistical functions while the second one uses the ELKI software providing users with development environment including algorithms of neural networks. The obtained results are similar to a certain extent which shows new possibilities of progressive use of neural networks in future and enables modern approach to analysing time series not only in agricultural sector.

Keywords

Comparative analysis, cereals production, ELKI software, Excel spreadsheet, neural networks, predicting, statistics, time series, trends.

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Introduction

In the area of the Czech Republic, common cereals – wheat, rye, barley, and oats – always have dominated and represented amount of 50%–60% of the whole crop farming volume (Liu et al., 2005). In the course of their existence, the statistical records show significant fluctuating of yield values in the period of 1920–2018 and prove no definite trend (Kůst and Záruba, 2020). Also volume proportions of individual crops constantly have changed. In the beginning, rye as a source of flour for baking of bread was the most grown plant but it was gradually replaced by wheat similarly as in the case of oats previously bountifully used as feedstuff for farm animals (Némethová et al., 2004). The area of fields for production of barley largely used in the beer industry decreased too while the area for wheat production increased for 240% of pre-war level (Hruška 2019). Development of maize production in the Czech Republic is interesting – since the fifties, area for production of maize used predominantly for ensilaging began to extend together with applying of artificial fertilizers while by the end of the eighties a significant decrease came. However, arrival of the new millennium brought considerable boom in maize growing because this crop became a strategic item as a fuel for biogas power stations producing renewable energy (Hruška, 2014).

Also the total area of agricultural land has changed in the course of time. Post-war area decrease due to topsoil occupation for extending cities and industrial complexes continued not until the end of the eighties (Šťastný, 2011). On the other hand, intensity of agricultural production increased. After 1989, the decrease accelerated and, just before the Czech accession to the EU in 2004, the total area of the agricultural land decreased to 2.6 million hectares (Hruška, 2014). However, not due to occupation for construction industry but for reasons of massive extensive swarding namely in submontane and montane regions.

This paper provides descriptions of two very different methodologies for forecasting of cereals production trends (for both entities – total and individual crops): forecasting by means of spreadsheet (Excel) using conventional mathematical and statistical functions and the ELKI software using neural networks algorithms (Phillips and Hansen, 2001). Both methods work with the identical input data adopted from the Czech Statistic Office data (Czech Statistic Office, 2019). All results are shown in transparent diagrams and accompanied by comparative analysis explaining differences between the results of both methods (Brožová and Beranová, 2017).

Materials and methods

Forecasting by means of Excel spreadsheet

For predicting future development of time series, the MS-Excel spreadsheet ranks among the best commonly available software tools (Köppelová and Jindrová, 2017). For such the calculating, the spreadsheet use the method of exponential smoothing (Kačer, 2013). At this method, time series are being replaced by different mathematic curves and, concurrently, the weights of individual records are exponentially decreased pastwards. In fact, it works as low-pass filtering when high-frequency noise is eliminated.

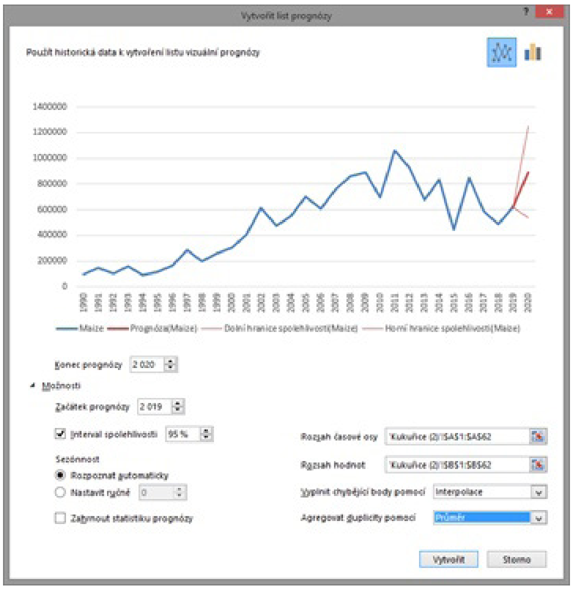

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Figure 1: Setup in Excel Create Forecast Worksheet dialogue box.

The guide to the *Create Forecast Worksheet (List prognózy)* provides analysts with possibility to set prognosing process parameters and, then, the function creates a new sheet containing both historical and predicated values including a diagram (see Figure 1). For prognoses of trends in cereal production in the Czech Republic, the following parameters were setup – *Forecast End (Konec prognózy)*: 2050; *Forecast Start (Začátek prognózy)*: 2020; *Confidence interval (Interval spolehlivosti)*: 95%; *Seasonality Detect (Sezónnost):* Detect Automatically (Rozpoznat automaticky); *Include Forecasts Statistics (Zahrnout statistiku prognózy)*: No; *Timeline Range & Values Range (Rozsah časové osy a Rozsah hodnot)*: automatically detected by Excel; *Fill Missing Points Using (Vyplnit chybějící body pomocí)*: Interpolation (Interpolace); *Aggregate Duplicates Using (Agregovat duplicita pomocí)*: Average (Průměr). The FORECAST.ETS function calculates values based on entered arguments (forecast start, historical data, timeline, seasonality, forecast end, aggregation) using exponential smoothing while the FORECAST.ETS.CONFIT function calculates the confidence interval showing how many percent for future points come under into the future result range (the narrower intervals the more accurate results) (Melart, 2016).

Forecasting by means ELKI software – Neural networks

The Java-based ELKI software represents a free software machine learning library for the Java programming language. ELKI represents a modular system with the object-oriented architecture integrating different components for machine learning and data mining by means its excellent modular data flow processing design. ELKI provides a competitive method against traditional methods by means of special algorithms representing neural networks as, for example, arbitrary algorithms, data types, distance functions, indexes, and evaluation measures. The application uses self-learning using sample data that may contain unknown or hardly expressible inner contexts that can be loaded by noise. Ability of noise filtering and finding of natural development relations belong to its most significant properties for processing of prognostic problems (Allen, 1994). Multi-level artificial neuron networks represent universal approximating (both linear and non-linear) tool usable for creating an *n*-variables function model in the course of learning process based on sample data. For purposes of prognoses creating, it is possible to create differently difficult models, however, solving several basic problems (neuron network configuring, calculating function of neurons, precision of neuron network learning, etc.) is essential for successful use of the neuron network (Singireddy, 2010). In cases of simpler tasks, there is not need any mathematic prediction model – providing a neural network with a data set used to be enough, the network is able to choice its own model (mostly very appropriate one). The numbers of inputs and outputs are given by a type of neural networks and represent two basic configuration parameters (Kačer, 2013).

However, creating of some approximation model of a multivariable function is essential for using a multi-level neural network. Network configuration (i.e. number of both input and output neurons, total number of neurons, number of neurons in hidden layer, number of hidden layers, and calculating function) affect the model properties. On Figure 2, there is a scheme of n-layer network modelling O_i $(x_1, x_2, ..., x_p)$ functions.

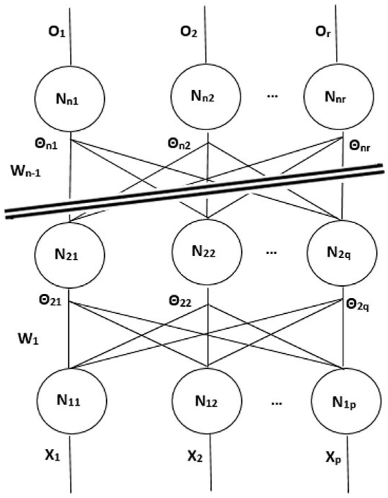

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Figure 2: Scheme of n-layer network modelling O_i functions.

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

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

In total, it means

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

of parameters represented by weights W_i and threshold values Θ_i. The numerous neurons within hidden layers the higher number of parameters and, concurrently, better possibilities of modelling of more complex functions. However, only hidden layer with $q \geq \min(p, r)$ or $q = \max(p, r)$ neurons is enough for most of tasks. In the case of equality in the expression $q \geq \min(p, r)$, minimizing of number of neurons in hidden layers is ensured, however, network learning may be worse (more learning sessions may be required). For the reason, the expression $q = \max(p, r)$ should be used in the beginning and, subsequently, a number of neurons or even layers may be decreased or increased. A function of neurons also affects the model properties (Kačer, 2013). For the purpose, the activation functions

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

or

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

or

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

are used.

To minimize a value of the error function, the method of backward error spreading is processed through learning of the multi-level neural network based on samples (learning with teacher) (Köppelová and Jindrová, 2019).

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

where $Y_j^{\circ}(X_i)$ is a required value while Y_j (X_i) is a real value of the j-th output at inputs given by the X_i vector. The learning process is completed when the value of error function $E < E_0$ (entered value) is achieved when the absolute value of change of the error function for a given number of learning phases is lower than the entered value, i.e. $\frac{|\Delta E|}{N_e} \leq \delta$ (N_e – entered value) or after completing of requested number of repeating (Kačer, 2013).

A basic trend model is derived from general perspective on behaviour of a system with memory whose outputs are in a given time instance dependent on current inputs and inner states of the system (Rakhmatulin, 2020).

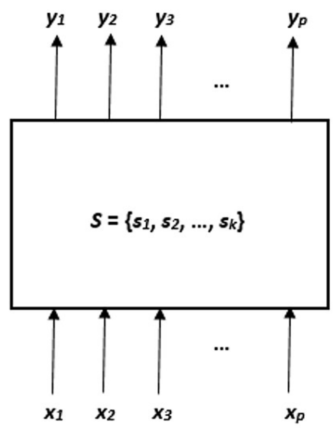

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Figure 3: Scheme of common system.

If $X = \{x_1, x_2, x_3, ..., x_p\}$ is the input vector (see Figure 3) and $S = \{s_1, s_2, s_3, ..., s_p\}$ is the vector of system inner states then the system outputs $Y = \{y_1, y_2, y_3, ..., y_p\}$ can be considered as dependencies $y_i(t) = f_i\ [X(t-1), S(t-1)]$ or $Y(t) = F\ [X(t-1), S(t-1)]$.

Generally, time series of multiple outputs or even input parameters (in the form of time series again) can be available for researching of future system behaviour (Šnorek and Jiřina, 1996). State values and, in most of cases, also system inputs are unknown and, that is why, they are almost undetectable and, therefore, it is not possible to create any prognostic model in any direct way (Köppelová and Svatošová, 2019). In the case of unavailable values of system states and inputs, it is necessary to express the assumption that an appropriate information is included in the output values because each value of output time series is dependent on the system states and inputs (Kačer, 2013). The model function for prediction of future values of time series Y can be formally expressed as:

$$Y(t) = \mathrm{F}\ [Y(t-1), Y(t-2), \dots, Y(t-k)], \tag{6}$$

where k represents a number of values of the time series used for prediction of a requested value. The expression (6) is a formal representation of the function of the prediction model with the neural network (see Figure 4). A default structure of the neural network for this prognostic model contains

$$N_{in} = r \cdot k \tag{7}$$

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

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

Formally, this expression represents a prognostic model shown on the Figures 2, 3 and 4. In this case, the neural network includes

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

input neurons; the same number of neurons is contained also in the hidden layer. The expressions (6) and (8) are representatives of structures of learning files of the appropriate models. After learning process, the neural network is used in calculating mode in which one value of Y(t) outputs is calculated based on the last k values of time series X and Y and p input values $X(t)$. By completing of the calculated values into the appropriate time series, it is possible to carry out any number of prediction steps and, so, to obtain a development prognosis of an appropriate quantity for longer time period (Kung et al., 2018).

The configuration of multi-layer neural networks consist in determining of network inputs and outputs, hidden layers, and neurons in them. The higher amount of parameter the more complex network and, concurrently, possibility of more precise modelling of the requested function defined by a remainder of time series. However, too high value of the parameter need not increase model quality and, vice versa, too lower value may cause excessive filtration – that is why some optimum value at which the model function is the best should

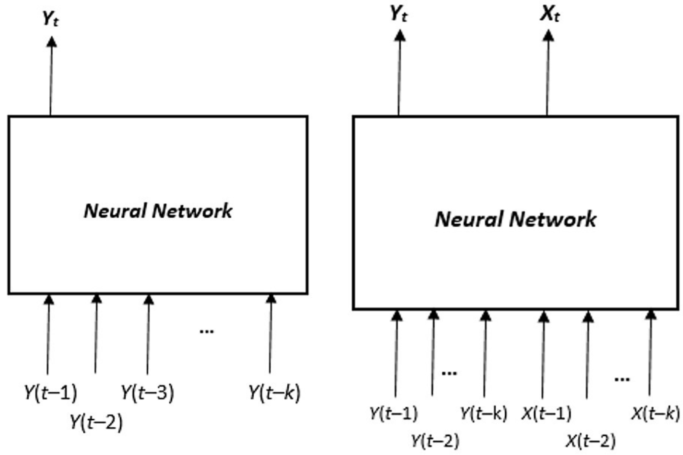

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Figure 4: Basic trend models.

be chosen (Kačer, 2013). Mostly, the models based on multi-layer neuron networks with only hidden layer used to be enough. In the case of neuron linear function, a network with only input and output layer is enough because more complex networks can be transformed to the function of such the simple neuron network.

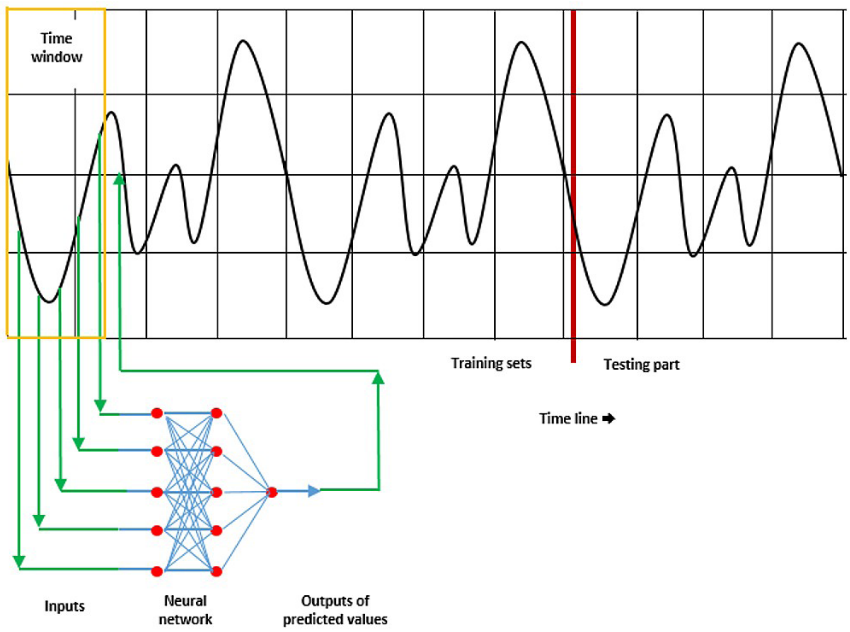
In the phase of learning of the neural network (with determined numbers of neurons in layers and their relations and transformation function) with a teacher, the values of weights and thresholds are progressively set up. After processing of input data, the outputs are compared with the requested outputs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

$$E_p = \frac{1}{2}(Y_n^p - Y_n)^2, \qquad (6)$$

where Y_n is the last value of the explored time series and Y_n^p is the value predicted by the model. By minimizing of the function $E_p(E)$, the optimum value (with minimum E_p) of neuron network learning is found (Yao et al., 2017). If no satisfactory result is achieved, then it is possible to change the value of parameter k, neuronal function, or even a number of network layers.

A testing set is created directly from time series so that inputs are represented by a certain number of recorded values and requested outputs by values in the specific distance from the input values. The input part represents a time window while the output part is a predicted value. Offsetting the time window along the time line creates items of the training set (see Figure 5). A part of the recorded set ought to be let for testing purposes which means this part of the time series should not be used during learning phase but during of testing of actual learning status (Obitko, 2019). Further, the completed training set has to be adjusted for use with a particular neural network (recalculating obtained values into the certain interval, etc.).

The disposable data are often classified to a learning set, validating set, and testing set. These three sets can be overlaid (see Figure 5) and need not be coherent. The learning set is a progression introduce to the network serving for its follow-up adjusting (Niedbała, 2019). The deviations contained in answers is used as a criterion for completing of the learning process. Afterwards, the testing set is used for testing of actual "knowledge" status applied for predicting future (formerly "unseen") values. So, the learning set serves for model searching, the validation set for model validating, and the testing set for testing of the applicability (Figure 6).



Source: Obitko (1999).

Figure 5: Creating training sets.

Data pre-processing represents an important part of the whole process. For example, removing trends or seasonal component (of course if identifiable) is of particular appropriateness. The neural networks with outputs falling within the fixed boundaries show only poor serviceability in predicting of values falling out of the intervals specified in advance. Then, the correctly configured neural network is able to solve various tasks.

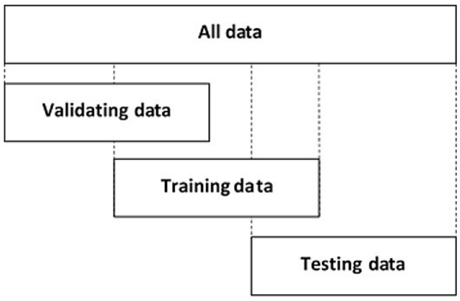


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Figure 6: Scheme of arrangement of data sets.

Data pre-processing represents an important part of the whole process. For example, removing trends or seasonal component (of course if identifiable) is of particular appropriateness. The neural networks with outputs falling within the fixed boundaries show only poor serviceability in predicting of values falling out of the intervals specified in advance. Then, the correctly configured neural network is able to solve various tasks.

Results and discussion

Resulting diagrams (Figures 7-12) include three data categories originating from preceding table pairs: historical data (Tables 1-6) based on data of the Czech Statistic Office (*Year, Production*), predicted data (*Prognosis, Lower Endpoint, Upper Endpoint*) calculated by means of Excel´s *Create Forecast Worksheet* procedure, and data predicted by help of ELKI neural networks (*Neural Network*).

While the data originating from the Czech Statistic Office provided the spreadsheet with inputs for calculating the first type of prognosis including lower and upper endpoints (table columns and diagram curves named *Prognosis, Lower Endpoint, Upper Endpoint*), the columns of values calculated within the environment of the ELKI neural network software (named *Neural Network*) were copied into the sheet additionally so that they can be processed into the integrated diagrams.

In all cases, the results generated by means of the neural network are more or less similar to prognoses values calculated by the spreadsheet. Neither lower nor upper endpoints variants were processed by the neural networks because only trend prognoses represented the purpose of the comparative analysis.

Cereals (total)

The production prognosis of all main kinds of cereals (wheat, rye, barley, oats, and maize) show only a very moderate increase (Köppelová and Jindrová, 2019). The neural networks prognosis fluctuates a bit form the main prognosis generated by means of the exponential smoothing method (Table 1, 2; Figure 7).

Wheat

The wheat production prognosis moderately rises while neural network prognosis shows relatively lesser deviations than in the case of total cereals production (Table 3, 4; Figure 8).

Rye

The rye production prognosis rapidly decreases, lower endpoint soon achieves zero level followed by main prediction generated by spreadsheet and neural networks. In fact, the zero values represented negative values and, for the purpose of rational interpreting the data they were transformed to zero level (Table 5, 6; Figure 9).

Year	Production (t)	Year	Production (t)	Year	Production (t)
1990	8946879	2000	6454237	2010	6877619
1991	7845290	2001	7337589	2011	8284806
1992	6564898	2002	6770829	2012	6595493
1993	6467852	2003	5762396	2013	7512612
1994	6777231	2004	8783801	2014	8779299
1995	6601711	2005	7659851	2015	8183512
1996	6644145	2006	6386078	2016	8596408
1997	6982772	2007	7152861	2017	7456779
1998	6668920	2008	8369503	2018	6970919
1999	6928371	2009	7831998	2019	7646148

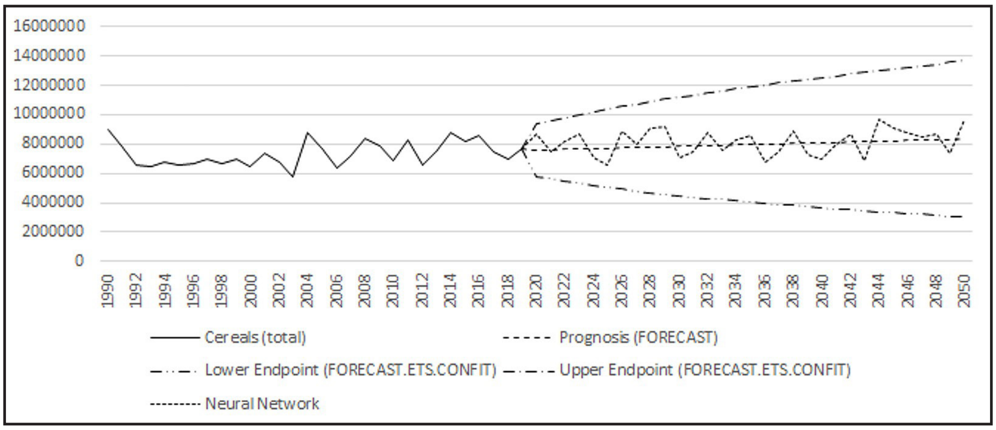
Source: CSO

Table 1: Total cereals production in period of 1990–2020.

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2020	7646148	7646148	7646148	7646148
2021	7619229	5632248	9606211	7472624
2022	7644466	5466529	9822402	8189064
2023	7669702	5315580	10023824	8636399
2024	7694938	5176297	10213579	7104460
2025	7720175	5046525	10393824	6597024
2026	7745411	4924695	10566126	8885206
2027	7770647	4809622	10731672	8024484
2028	7795883	4700386	10891381	9062427
2029	7821120	4596255	11045984	9164711
2030	7846356	4496637	11196075	7111268
2031	7871592	4401045	11342140	7491012
2032	7896828	4309070	11484587	8748790
2033	7922065	4220368	11623762	7625641
2034	7947301	4134644	11759958	8247687
2035	7972537	4051646	11893428	8531530
2036	7997773	3971152	12024395	6766181
2037	8023010	3892970	12153049	7510691
2038	8048246	3816929	12279563	8846229
2039	8073482	3742878	12404087	7278906
2040	8098718	3670682	12526755	6953007
2041	8123955	3600222	12647688	7965763
2042	8149191	3531388	12766994	8706416
2043	8174427	3464083	12884772	6849893
2044	8199664	3398216	13001111	9672900
2045	8224900	3333708	13116091	9096176
2046	8250136	3270485	13229788	8782732
2047	8275372	3208477	13342268	8463229
2048	8300609	3147623	13453594	8674356
2049	8325845	3087866	13563824	7413610
2050	8351081	3029152	13673010	9726782

Source: CSO and author´s procession

Table 2: Prognoses of total cereals production in period of 2020–2050 by means of ETS algorithm and neural network.



Source: CSO and author´s procession

Figure 7: Prognoses of total cereals production by means of ETS algorithm and neural network.

Year	Production (t)	Year	Production (t)	Year	Production (t)
1990	4624190	2000	4084107	2010	4161553
1991	4081279	2001	4476080	2011	4913048
1992	3412943	2002	3866473	2012	3518896
1993	3304271	2003	2637891	2013	4700696
1994	3713476	2004	5042523	2014	5442349
1995	3822769	2005	4145039	2015	5274272
1996	3727203	2006	3506252	2016	5454663
1997	3640269	2007	3938924	2017	4718205
1998	3844741	2008	4631502	2018	4417841
1999	4028271	2009	4358073	2019	4812163

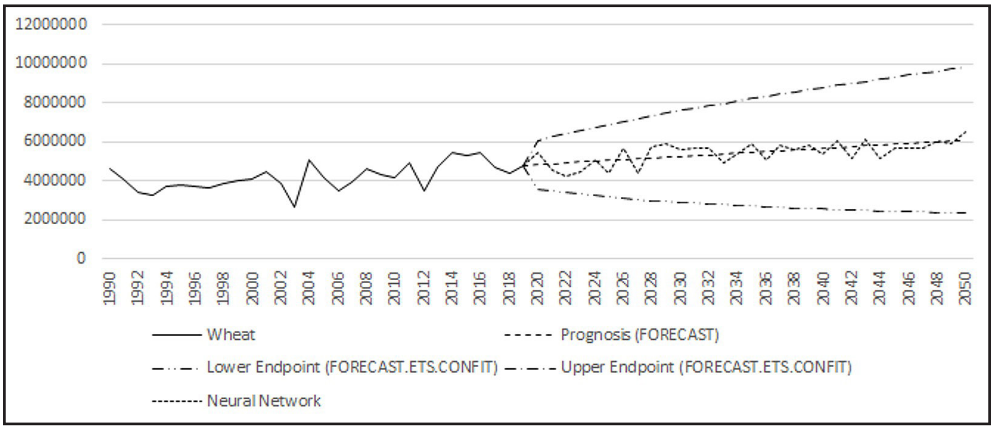
Source: CSO

Table 3: Wheat production in period of 1990–2020 .

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2020	4842851	3597441	6088260	5420868
2021	4884370	3491402	6277337	4561171
2022	4925889	3399053	6452725	4261918
2023	4967407	3317057	6617758	4493976
2024	5008926	3243241	6774612	5114009
2025	5050445	3176092	6924799	4369862
2026	5091964	3114510	7069418	5689983
2027	5133483	3057665	7209301	4395625
2028	5175002	3004912	7345091	5754819
2029	5216521	2955739	7477303	5872656
2030	5258040	2909729	7606350	5621003
2031	5299559	2866542	7732576	5689307
2032	5341078	2825890	7856265	5672014
2033	5382596	2787533	7977660	4944172
2034	5424115	2751264	8096967	5417156
2035	5465634	2716905	8214363	5899624
2036	5507153	2684302	8330004	5048731
2037	5548672	2653320	8444024	5861215
2038	5590191	2623839	8556543	5581260
2039	5631710	2595752	8667667	5836822
2040	5673229	2568967	8777490	5370144
2041	5714748	2543398	8886097	6066215
2042	5756267	2518970	8993564	5171722
2043	5797785	2495612	9099959	6158083
2044	5839304	2473264	9205345	5147530
2045	5880823	2451868	9309778	5711101
2046	5922342	2431372	9413312	5716505
2047	5963861	2411729	9515993	5711375
2048	6005380	2392895	9617865	6075366
2049	6046899	2374830	9718968	5929710
2050	6088418	2357495	9819340	6532677

Source: CSO and author´s procession

Table 4: Prognoses of wheat production in period of 2020–2050 by means of ETS algorithm and neural network



Source: CSO and author´s procession

Figure 8: Prognoses of wheat production by means of ETS algorithm and neural.

Year	Production (t)	Year	Production (t)	Year	Production (t)
1990	557712	2000	150052	2010	118233
1991	352992	2001	149298	2011	118456
1992	240067	2002	119154	2012	146962
1993	256079	2003	159312	2013	176278
1994	275654	2004	313348	2014	129059
1995	261938	2005	196755	2015	107874
1996	204279	2006	74811	2016	104353
1997	259412	2007	177507	2017	109241
1998	261167	2008	209787	2018	120160
1999	202373	2009	178070	2019	157561

Source: CSO

Table 5: Rye production in period of 1990–2020.

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2020	144828	9438	280218	56499
2021	136842	0	319081	243279
2022	128855	0	348230	56657
2023	120869	0	372010	213594
2024	112882	0	392260	155000
2025	104896	0	409962	188309
2026	96910	0	425713	47492
2027	88923	0	439909	166332
2028	80937	0	452829	4105
2029	72950	0	464677	104978
2030	64964	0	475609	114772
2031	56978	0	485746	167245
2032	48991	0	495185	148549
2033	41005	0	504004	124401
2034	33018	0	512270	3138
2035	25032	0	520036	0

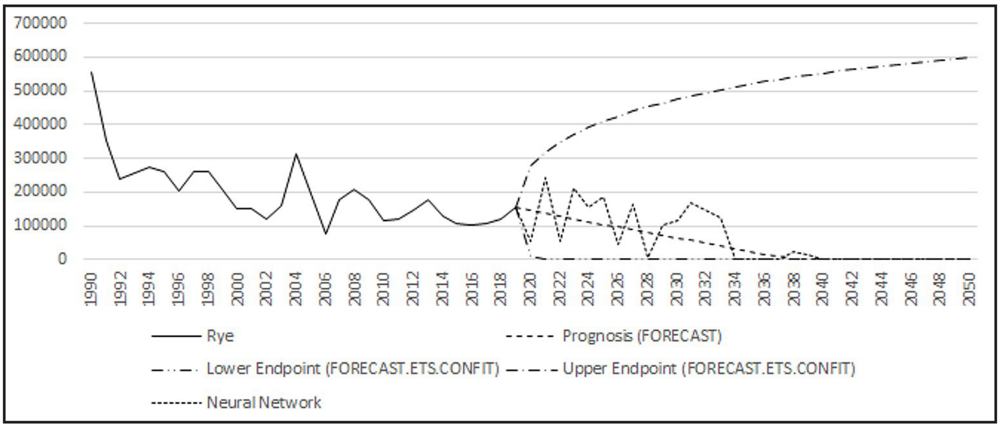
Source: CSO and author´s procession

Table 6: Prognoses of rye production in period of 2020–2050 by means of ETS algorithm and neural network (to be continued).

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2036	17046	0	527348	0
2037	9059	0	534248	0
2038	1073	0	540767	24538
2039	0	0	546938	14954
2040	0	0	552785	0
2041	0	0	558332	3928
2042	0	0	563600	0
2043	0	0	568606	0
2044	0	0	573367	0
2045	0	0	577899	0
2046	0	0	582213	0
2047	0	0	586324	0
2048	0	0	590241	0
2049	0	0	593975	0
2050	0	0	597535	0

Source: CSO and author´s procession

Table 6: Prognoses of rye production in period of 2020–2050 by means of ETS algorithm and neural network (continuation).



Source: CSO and author´s procession

Figure 9: Prognoses of rye production by means of ETS algorithm and neural.

Barley

The barley production prognosis is very similar to rye one. Deviations of the curve generated by the neural network are more significant and, the values in the period 2034–2037 achieved negative values but, during 2038–2040, moderately rise to the positive ones again. It should be noted that it is only a demonstrative estimation and the real trend development may probably very differ (Table 7, 8; Figure 10).

Oats

Also the oats production prognosis show substantial decrease. Strong fluctuating the prognosis curve generated by the neural networks along the zero line is worth noticing. The predicted development is very similar to prognoses for rye and barley (Table 9, 10; Figure 11).

Maize

The maize production prognosis shows the fastest increase among another cereals. The markedly narrow area formed by the upper lower endpoints boundaries is caused by relatively more moderate fluctuating of values within the historical data. No values achieve the zero (negative) level (Table 11, 12; Figure 12).

Year	Production (t)	Year	Production (t)	Year	Production (t)
1990	3157299	2000	1629372	2010	1584456
1991	2833023	2001	1965611	2011	1813679
1992	2512490	2002	1792557	2012	1616467
1993	2418517	2003	2068693	2013	1593760
1994	2419297	2004	2330582	2014	1967049
1995	2140487	2005	2195376	2015	1991415
1996	2262377	2006	1897703	2016	1845254
1997	2484548	2007	1893408	2017	1712279
1998	2093101	2008	2243865	2018	1606034
1999	2137376	2009	2003032	2019	1718061

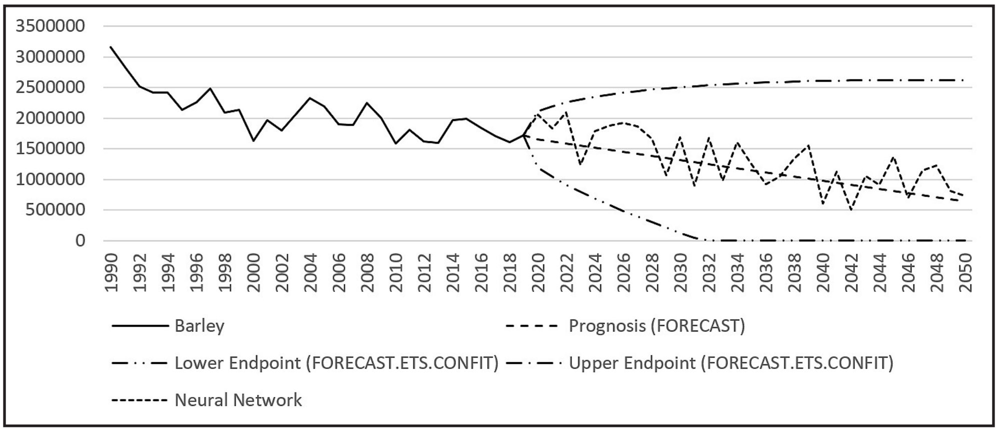
Source: CSO

Table 7: Barley production in period of 1990–2020.

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2020	1718061	1718061	1718061	1718061
2021	1654066	1194395	2113736	2059985
2022	1620213	1045349	2195077	1832993
2023	1586360	915571	2257149	2096418
2024	1552507	797679	2307334	1241298
2025	1518654	688057	2349250	1783129
2026	1484801	584615	2384987	1874070
2027	1450948	486013	2415882	1916401
2028	1417095	391336	2442854	1860193
2029	1383242	299920	2466563	1667709
2030	1349389	211272	2487506	1068591
2031	1315536	125009	2506063	1686187
2032	1281683	40828	2522538	901426
2033	1247830	0	2537175	1672136
2034	1213977	0	2550173	975554
2035	1180124	0	2561700	1604940
2036	1146271	0	2571897	1249923
2037	1112418	0	2580883	920515
2038	1078565	0	2588761	1043732
2039	1044712	0	2595622	1339926
2040	1010859	0	2601542	1552994
2041	977006	0	2606592	605118
2042	943153	0	2610832	1125660
2043	909300	0	2614317	503165
2044	875447	0	2617096	1053293
2045	841594	0	2619211	905003
2046	807741	0	2620704	1374970
2047	773888	0	2621609	701877
2048	740035	0	2621959	1150383
2049	706182	0	2621784	1228320
2050	672329	0	2621112	812955

Source: CSO and author´s procession

Table 8: Prognoses of barley production in period of 2020–2050 by means of ETS algorithm and neural network.



Source: CSO and author´s procession

Figure 10: Prognoses of barley production by means of ETS algorithm and neural.

Year	Production (t)	Year	Production (t)	Year	Production (t)
1990	373951	2000	135858	2010	138224
1991	301682	2001	136363	2011	164248
1992	207918	2002	167708	2012	171976
1993	262594	2003	233560	2013	139120
1994	207562	2004	227017	2014	152232
1995	186693	2005	151054	2015	154576
1996	214163	2006	154906	2016	132220
1997	246637	2007	159408	2017	142441
1998	179671	2008	155868	2018	152656
1999	179130	2009	165993	2019	134410

Source: CSO

Table 9: Oats production in period of 1990–2020.

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2020	130964	57845	204084	137016
2021	126319	27899	224740	183063
2022	121674	3198	240150	110438
2023	117029	0	252661	133952
2024	112384	0	263265	92507
2025	107739	0	272493	118497
2026	103094	0	280668	138850
2027	98449	0	288003	132575
2028	93804	0	294649	49956
2029	89159	0	300716	53343
2030	84513	0	306288	78769
2031	79868	0	311430	128041
2032	75223	0	316196	41318
2033	70578	0	320627	42248
2034	65933	0	324759	0
2035	61288	0	328621	0
2036	56643	0	332238	42730

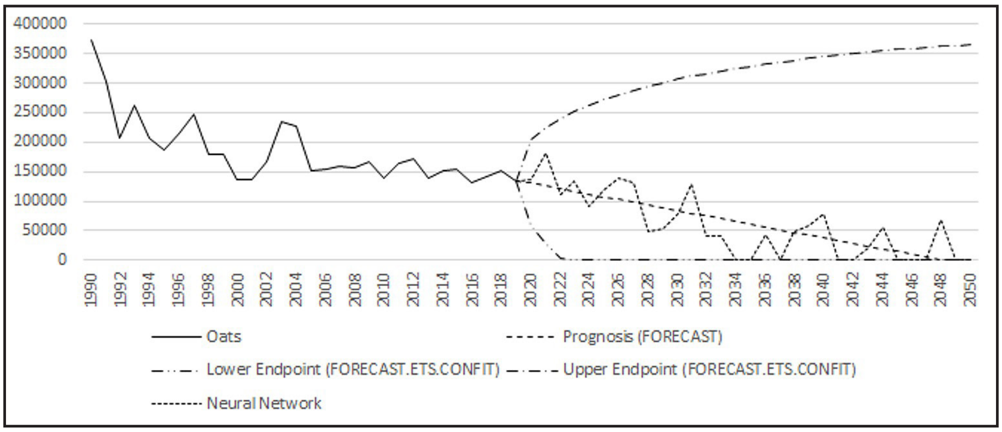
Source: CSO and author´s procession

Table 10: Prognoses of oats production in period of 2020–2050 by means of ETS algorithm and neural network (to be continued)..

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2037	51998	0	335632	0
2038	47353	0	338822	47501
2039	42708	0	341822	58217
2040	38063	0	344648	78054
2041	33418	0	347312	0
2042	28772	0	349825	0
2043	24127	0	352196	21724
2044	19482	0	354436	56082
2045	14837	0	356551	0
2046	10192	0	358550	0
2047	5547	0	360438	0
2048	902	0	362221	68870
2049	0	0	363906	0
2050	0	0	365496	0

Source: CSO and author´s procession

Table 10: Prognoses of oats production in period of 2020–2050 by means of ETS algorithm and neural network (continuation).



Source: CSO and author´s procession

Figure 11: Prognoses of oats production by means of ETS algorithm and neural.

Year	Production (t)	Year	Production (t)	Year	Production (t)
1990	98 381	2000	303 957	2010	692 589
1991	150 280	2001	408 653	2011	1 063 736
1992	103 720	2002	616 234	2012	928 147
1993	157 045	2003	476 371	2013	675 380
1994	91 396	2004	551 628	2014	832 235
1995	113 274	2005	702 933	2015	442 709
1996	168 684	2006	606 366	2016	845 765
1997	285 199	2007	758 781	2017	588 105
1998	200 562	2008	858 407	2018	489 154
1999	260 495	2009	889 574	2019	620 261

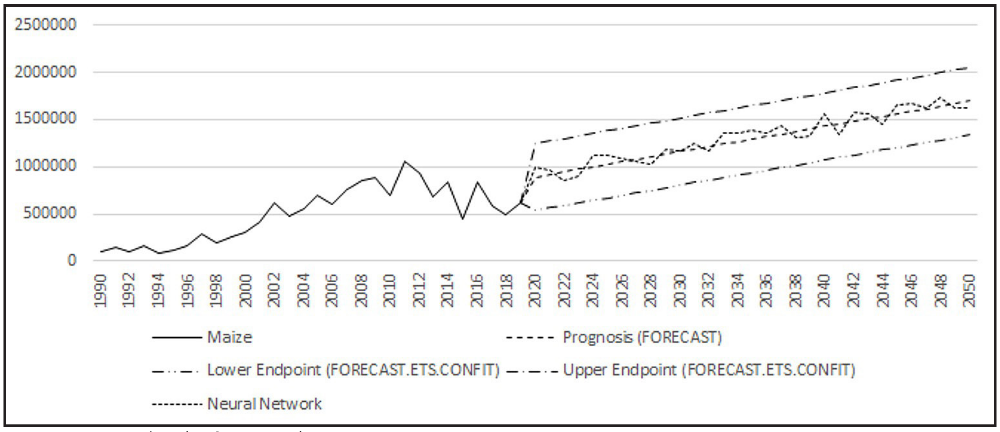
Source: CSO

Table 11: Maize production in period of 1990–2020.

Year	Prognosis	Lower Endpoint	Upper Endpoint	Neural Network
2020	620261	620261	620261	620261
2021	892918	538191	1247645	995787
2022	919649	564920	1274378	969326
2023	946380	591648	1301111	854520
2024	973111	618375	1327847	906091
2025	999842	645099	1354584	1124663
2026	1026573	671821	1381324	1113504
2027	1053303	698541	1408066	1085446
2028	1080034	725257	1434811	1055633
2029	1106765	751971	1461560	1019528
2030	1133496	778680	1488312	1188281
2031	1160227	805385	1515069	1161344
2032	1186958	832086	1541830	1249997
2033	1213689	858782	1568595	1173140
2034	1240420	885474	1595366	1351433
2035	1267151	912159	1622142	1356723
2036	1293882	938839	1648924	1394545
2037	1320612	965512	1675713	1353286
2038	1347343	992179	1702508	1427776
2039	1374074	1018839	1729309	1314321
2040	1400805	1045492	1756118	1330463
2041	1427536	1072137	1782935	1554812
2042	1454267	1098775	1809759	1346256
2043	1480998	1125403	1836592	1570944
2044	1507729	1152024	1863434	1562646
2045	1534460	1178635	1890284	1449037
2046	1561191	1205237	1917144	1656066
2047	1587922	1231830	1944013	1666688
2048	1614652	1258412	1970893	1628380
2049	1641383	1284984	1997783	1737036
2050	1668114	1311545	2024683	1626713

Source: CSO and author´s procession

Table 12: Prognoses of maize production in period of 2020–2050 by means of ETS algorithm and neural network.



Source: CSO and author´s procession

Figure 12: Prognoses of maize production by means of ETS algorithm and neural.

Conclusion

At prediction of results of cereals production trends, it is not possible to expect absolutely exact answers. Models based on perceptron neural networks substitute paradigmatic states of interpolating functions significantly dependent on network configuration (Pattreson, 1996). Processing the same sets of input data and consequent providing with very similar output values clearly prove that neural networks can be used for forecasting of development of certain types of agricultural trends in a similar way as standard statistic prognostic methods.

Furthermore, neural networks are able to generalize solved problems and are more resistant to noise. On the other hand, there is not possible to exactly determine what did an used neural network learnt and, that is why, it is very difficult to find error estimation (Chen, 2005). When any description of observed quantity are available then use of neural network may be an ideal way. Evaluation of tools for prediction may be quite complicated because, in the case of statistic procedures, there are ready heuristics available unlike in the case of neural networks where there is no complete heuristics of methods, modelling over processed data, and configuring parameters for individual network types (Malinovský, 2020, Yao et al., 2017). Within the scope of testing individual parameters, it is impossible to determine some certain network configuration providing with the best results. Quality of prediction carried out by an artificial neural network is affected by lot of factors with potential positive influence on prediction quality (Kabáth, 2009). The factors include number of learning phases, selection of training, testing, and validating set, use of different time series for learning, way of learning, etc. Architectures of neural networks may be easily changed by operators and, so, they enable experimenting with configuration.

Neural networks represent an alternative way to exact statistic (mathematic) methods within the field of forecasting of agricultural trends as well as within other ones.

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