Sustainable Development Forecasting of the Agricultural Sector using Machine Learning

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Abstract: Sustainable development paradigm is a combination of economic, social and environmental components represented by a significant number of interconnected factors. Their comprehensive impact determines the ways and dynamics of achieving sustainable development goals. Sustainable development forecasting is accompanied by the analysis and processing of a significant set of indicators and requires special methods of data processing. The neural network modelling allowed to form a multifactorial impact model on the final indicator, namely labour productivity, according to the sustainable development goals. The proposed model allows not only to model and forecast, based on the previously obtained indicators and their dynamics, but also to set target benchmarks to obtain a range of possible scenarios of system development, which depends on the forecasting conditions and parameters. They do not only increase the validity of managerial decision-making, but also ensures relevant adaptation of the management object to the changing environment, affects not only the final result, but also the process of its achievement, including optimization of sustainable development levers.

1 INTRODUCTION

The global goal of sustainable development is harmonization of economic, social and environmental trends of mankind`s way of life; targeting general well-being due to the ecologically balanced and socially-oriented economy. The main goal of sustainable development is providing food for the population of Earth, so the most relevant and developed sectoral level problem is of sustainable development for the agro-industrial complex.

Permanent growth of agricultural production, better rural quality of life and environmental preservation are the determinants of economic growth of the national agricultural sector and its sustainable development. Human capital acts as a determining lever of the national economic growth in general and the agrarian sector, in particular, by implementing labour. It causes lower production costs, higher productivity and profits, leads to accumulation of production capital, which ensures sustainable development of the national economy.

Rapid economic development and quality of life improvement are achieved in close connection with sustainable development, but require effective management of natural and technological resources at both global, regional, national or local levels. New challenges and sustainable development indicators are constantly emerging, which require setting the priority for each problem`s decision-making. Since these indicators are characterized by uncertainty, vague vision of new problems and indicators`

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interconnection, it is preferable to analyze them using forecasting models with hidden information, which cannot be perceived by means of classical analysis (Al'mukhamedova, 2021).

The paradigm of sustainable development is based on the combination of economic, social and environmental components represented by a significant number of interconnected factors. Its comprehensive action determines the ways and dynamics of achieving sustainable development goals. Managerial decision-making referring to each impact factor, taking into account their interaction has to be accompanied by the analysis, and processing of a significant set of data requiring special methods of information processing. Solving this problem is possible using machine learning and parameters` assessment, which will be considered in the model.

To determine the levers of influence on the target indices of sustainable development in the agrarian sector, one of which is labour productivity in agriculture, it is necessary to evaluate sustainable development determinants.

The method of artificial neural network can be used for research. The following stages characterize the method (Zaporozhchenko et al., 2019):

- search of data;
- preparation and normalization of data;
- choice of type of neuron network;
- experimental choice of network characteristics;
- experimental choice of parameters;
- obtaining an artificial neuron network for modeling the labour productivity;
- checking of adequacy of the model;
- adjustment of parameters,
- final network training using learning sampling;
- adaptation of a neural network caused by changes in weight coefficients reflecting network interconnection and network configuration adjustment.

2 METHODOLOGY

Among the currently known models and forecasting methods are (Bizianov, 2021): multiplicative models, dynamic linear and nonlinear models, threshold autoregressive models, Kalman filters, time series, ARMAX models, nonparametric regression models, artificial neural networks (ANNs), statistical models, as well as hybrid models, for example, fuzzy artificial neural networks (NNNs).

Various types of regressions and the models generated from them, as well as time series, can be effectively used in cases where the dependence of the predicted indicator over time is continuous, has a smooth character and does not contain jumps and gaps. In the case of forecasting based on non-periodic data series, in order to obtain an acceptable accuracy (at least a few percent), one has to take into account a significant number of terms of the series or regression coefficients. In addition, when processing non-periodic signals, both regression and time series give adequate results only within the interpolation interval.

Artificial neural networks are more flexible than the above models, due to the presence in them of a complete relationship between input and intermediate variables, as well as the possibility of introducing non-linearity into the activation functions (Khaykin, 2006). This explains their expanding application in solving computational, statistical, prognostic and other problems. The disadvantage of “classical” ANNs is that for their training it is necessary to have a sufficiently large amount of initial data, which is not always possible.

Linear methods are traditionally used for macroeconomic forecasting. One of their disadvantages is not taking into account hidden linear relationships between model input parameters.

Forecasting makes it possible to obtain a set of possible scenarios for system`s development, which depends on the conditions and parameters of forecasting. It causes application of a wide range of methods, one of which is the method of artificial neural networks.

Artificial neural networks are quite effective when solving problems of predicting the behavior of complex systems and the selection of unknown parameters that link the characteristics of complex objects, including economic systems (Romanchukov, 2019).

Parameters characterizing economic, social and environmental impacts have been chosen as determinants (controlled parameters) affecting sustainable development in the agrarian sector. Labour productivity is considered as final indicator, which is a factor characterizing the efficiency of labour potential application. Input indicators for modelling by the method of artificial neural networks are the following:

Y - labour productivity, UAH per worker;

X_1 - average monthly nominal wage of full-time workers in agriculture, UAH;

X_2 - energy security (power capacities/sown area), kW/100 ha;

X_3 - power-weight ratio (power capacities /number of employees), kw/per capita;

X_4 - number of tractors per 100 hectares of sown area;

X_5 - number of tractors per 1,000 employees;

X_6 - mineral fertilizers per 1 hectare of sown area, kg (nutrients);

X_7 - organic fertilizers for agricultural crops, per 1 hectare of sown area, tons;

X_8 - stationary and mobile sources of air pollution, per capita, kg;

X_9 - total waste accumulated at landfill sites per capita, kg;

X_{10} - average index of regional human development;

X_{11} - capital investment per capita, UAH.

2.1 Data and Justification

2008-2019s statistical data was used to forecast sustainable development parameters. Labour productivity growth in agriculture was considered as a target value for the resulting indicator according to the sustainable development goals (relative to 2015) (Natsional'na dopovid', 2017). An adverse trend characterizes agriculture in Ukraine: labour productivity and average monthly nominal wage growth show ahead of wage rates (Fig. 1), which, in our opinion, brakes causal relationship (Vasyl'yeva, 2021): The rate of wage growth surpasses labour productivity growth rate (2008-2012). During 2013-2014, there was a positive tendency: labour productivity growth rate was ahead of wages growth rate. Wages growth rate has been surpassing the labour productivity growth rate since 2015.

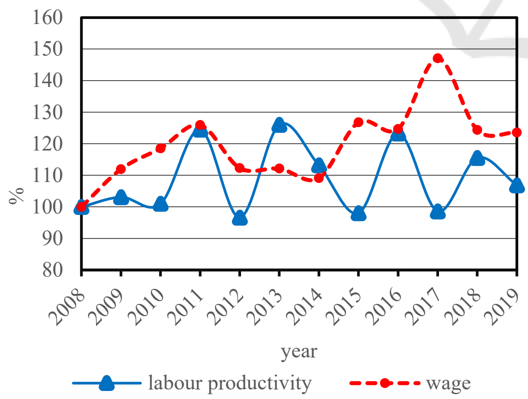

Figure 1: Chain growth rates of labour productivity and average monthly nominal wages in agriculture.

Thus, the formation of labour remuneration mechanisms in agriculture in Ukraine almost does not depend on the economic results, the employees fall short of labour remuneration in comparison with their efforts. Low productivity growth rates, in turn, do not form the background for higher income and better quality of life (Vasyl'yeva, 2021). Positive interdependence of productivity and remuneration allows us to conclude that it is necessary to include parameter X_1 (average monthly nominal wages of full-time workers in agriculture) into the model of labour potential assessment.

Scientific and technological progress, technical equipment, and latest technologies require certain level of personnel`s education and qualification being the determinants of staff efficiency. These qualitative characteristics of human resources can be described both by the integral index of regional human development (X_{10}) and by the production facilities and technologies applied by personnel when working (X_2- X_7).

Taking into account the influence of air pollution from stationary and mobile sources (X_8) and total waste accumulated at landfill sites (X_9) on economic growth fully corresponds to the sustainable development trend, we consider these parameters relevant to be included into the model for the assessment and forecasting of labour potential in the agrarian sector amid sustainable development.

Labour productivity in the context of new economy is largely determined by qualitative characteristics of labour potential: level of formal and informal education, creativity, and well-being. Qualitative parameters of labour potential in the model are described using the average index of regional human development (X_{10}). The index has 33 indicators reduced to 6 subindexes (according to individual aspects of human development: reproduction of population; social position; comfortable life; welfare; worthwhile work; education) (Rehional'nyy lyuds'kyy rozvytok, 2018).

Besides, the amount of capital investment affects human development, being directed to the fixed assets` reproduction, introduction of technical progress, construction and reconstruction of social and cultural institutions (X_{11}).

Thus, the parameters affecting labour potential in the agrarian sector amid sustainable development (characterize economic, social and environmental impacts) have been substantiated for modelling.

2.2 Forecasting Models

Modelling of sustainable development determinants in the agricultural sector was carried out using a sample of 120 values of each indicator. A dynamic range of selected data represent the model`s input parameters. The correlation matrix of input parameters shows that the strongest correlation with other parameters occurs for X_1 (average monthly nominal wages of full-time employees in agriculture), X_3 (power-weight ratio), X_6 (mineral fertilizers), X_{10} (average regional human development index), and X_{11} (capital investment) (Fig. 2).

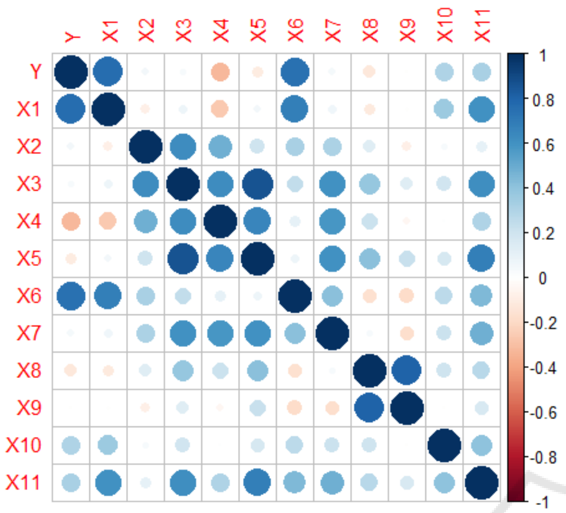

Figure 2: The correlation matrix of input parameters of sustainable development.

The correlation confirms the relationship between the selected parameters: higher power-weight ratio, bigger number of tractors and growth of soil mineralization increase gross output and labour productivity, which are the basis for higher wages; the growth of the human development index, capital investment in education, and health care increase the level of labour potential and its productivity. The parameters X_4 (number of tractors) and X_8 (stationary and mobile sources of air pollution) have a negative impact on labour productivity. X_9 factor (total waste accumulated at landfill) does not affect the modelling result.

Thus, correlation analysis of statistical data has revealed the impact strength and the relationship reliability between the model`s factor variables and the final indicator of labour potential application, i.e. labour productivity.

2.2.1 Generalized Linear Model (GLM)

Generalized Linear Model is a universal method of building regression models, which allows to take into account factors` interaction, the type of distribution of a dependent variable and assumptions about the nature of regression dependence. GLM is a well-designed and easy-to-understand way to build models.

GLM has the next advantages when doing analysis in comparison with traditional methods:

- the ability to take into account complex types of factors` interaction;
- a wide choice of dependence function`s type;
- lack of requirements for the normality of the response variable`s distribution;
- statistical measurement of various factors` impact on the observed value;
- obtaining information on the reliability of the constructed model results.

2.2.2 Artificial Neural Network

Neural network algorithms and technologies as the latest modelling and forecasting methods applied for various economic processes have been actively developed (Al'mukhamedova, 2021; Dawes, 2022; Maehashi, 2020; Zaporozhchenko et al., 2019).

During network operation, the values of input variables are put to input elements. Then neurons of the intermediate and output layers start operating. Each of them assesses its value of activation, subtracting from the previous layer`s sum its threshold. Further step is to develop the activation function of the presented data, resulting in a neuron output signal. After performing all neurons` operations, the output value of the last neurons` layer is taken for the output value of the entire network.

The system, which could be taught about significant volumes of information, building correlations and functional dependencies, which cannot be detected when using other information processing methods, is one of the advantages of system`s forecasting based on artificial neural networks (ANN).

Neural network modelling benefit is neural networks` potential to find out optimal indicators for the tool and build optimal prediction strategy for the range. Moreover, these strategies can be adaptive, changing with external factors shift, which is especially important for the systemic phenomena of sustainable development.

2.2.3 Random Forest Algorithm

Modern ensemble methods of machine learning for the regression classification include the Random Forest method, which is to build an array ("forest") of decision-making trees, making an average forecast (regression) of the built trees. Random forest is a managed learning algorithm. Built "Forest" is an ensemble of decision trees, which is typically taught by the method of "bags". The general idea of the “bags” method is to combine learning models to increase the overall result.

3 RESULTS AND DISCUSSION

To check the statistical significance of the difference between model`s mean values of input parameters and to assess the probability of their interaction, the dispersion analysis of sustainable development parameters was carried out (Table 1).

The dispersion analysis revealed that parameters X_1 (average nominal wage of full-time employees in agriculture), X_4 (number of tractors per 100 hectares of sown area), X_6 (mineral fertilizers) have the biggest impact on labour productivity. X_3 (power-weight ratio) has somewhat smaller influence. X_2 parameter (energy security) is insignificant.

To build a generalized regression model (GLM), a linear model coefficients were calculated. Building of a generalized regression model in the Rstudio software environment:

```
Call:
glm(formula = Y ~ ., family = "gaussian", data = scaled_tr)
Deviance Residuals:
Min 1Q Median 3Q Max
-0.248644 -0.061787 0.002466 0.059341 0.281375.
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.25518 0.04391 5.811 6.35e-08***
X1 0.26334 0.10127 2.600 0.0106*
X2 -0.11443 0.49408 -0.232 0.8173
X3 0.25227 0.55407 0.455 0.6498
X4 -0.34562 0.19872 -1.739 0.0849
X5 0.02655 0.50460 0.053 0.9581
X6 0.67904 0.09670 7.022 2.03e-10***
X7 -0.09787 0.07328 -1.336 0.1845
X8 -0.10786 0.09928 -1.086 0.2797
X9 0.21204 0.12418 1.707 0.0906
X10 0.12414 0.06547 1.896 0.0606
X11 -0.25292 0.13467 -1.878 0.0631
Signif. codes: 0'***' 0.001'**' 0.01'*' 0.05'.' 0.1' ' 1
(Dispersion parameter for gaussian family taken to be 0.01255949).
```

The resulting equation of regression to find the resulting indicator (labour productivity) is presented as:

$$Y=0,25518+0,26334X_1-0,11443X_2+0,25227X_3-0,34562X_4+0,02655X_5+0,67904X_6-0,09787X_7-0,10786X_8+0,21204X_9+0,12414X_{10}-0,25292X_{11} \quad (1)$$

Visualization of the forecasting results by the method of the generalized regression model (Fig. 3).

A neural network consisting of three layers, each of which has seven, three and one direct propagation neurons was studied. As an optimization algorithm the method of reverse error distribution, the activation function of hidden layers` neurons – Sigmoid, output layer – linear, input initialization of scales – arbitrary, the loss function as the error sum of squares were used. Network learning consisted of finding and determining the weights of neurons (synaptic weights) that minimize the difference between the target variable and the outcome of the network (Derbentsev et al., 2020). To teach the network, a data set consisting of a set of input parameters and the desired output values (target value of labour productivity) was applied.

The study modelling was provided by the programming language R using the Rstudio software (free environment for software development with free input code for programming language R applied for statistical data processing and graphics) (Hornik, 2015). The weights of each layer`s neurons of the network after learning were obtained. The graphical illustration of the obtained neural network in the Rstudio environment is as follows (Fig. 4).

The model based on the decision tree "Random Forest"(Xie, 2020, Sinha, 2019), including 500 trees (combinations of parameter values) was analyzed too:

```
Call:
randomForest(formula = Y ~ ., data = scaled_tr, ntree = 500, mtry = 3, importance = TRUE, proximity = TRUE, oob.prox = FALSE.
Type of random forest: regression.
Number of trees: 500
No. of variables tried at each split: 3.
Mean of squared residuals: 0.01138498
% Var explained: 77.74.
```

The Random Forest method (Fig. 5, 6) also proves significant impact of parameters X_1 (average monthly nominal wages), X_6 (mineral fertilizers), X_5 (number of tractors), and X_{11} (capital investment) on the efficiency of labour potential in the agrarian sector (labour productivity).

The results of forecasting by the method of artificial neural networks and the method of Random forest in comparison with the modelled values are presented by Fig. 6,7, respectively.

Comparative analysis of artificial neural networks, Random forest method and generalized linear regression method for predicting sustainable development in the agricultural sector prove that each of these methods can be used (Table 2), but, in our opinion, the most appropriate is the application of artificial neural networks` method, as it has a number of advantages.

Table 1: Dispersion analysis of sustainable development parameters.

	Df	Sum Sq	Mean Sq	F value	Pr (>F)	
X_1	1	2,42E+11	2,42E+11	282,8	< 2E-16	***
X_2	1	5,75E+09	5,75E+09	6,731	0,0107	*
X_3	1	6,93E+09	6,93E+09	8,11	0,0052	**
X_4	1	1,13E+10	1,13E+10	13,251	0,0004	***
X_5	1	2,56E+09	2,56E+09	2,994	0,0864	.
X_6	1	4,70E+10	4,70E+10	54,978	2,90E-11	***
X_7	1	2,84E+09	2,84E+09	3,322	0,0711	.
X_8	1	3,15E+08	3,15E+08	0,369	0,545	
X_9	1	1,44E+09	1,44E+09	1,683	0,1973	
X_{10}	1	2,45E+09	2,45E+09	2,861	0,0936	.
X_{11}	1	3,02E+09	3,02E+09	3,527	0,0630	.
Residuals	108	9,23E+10	8,55E+08			

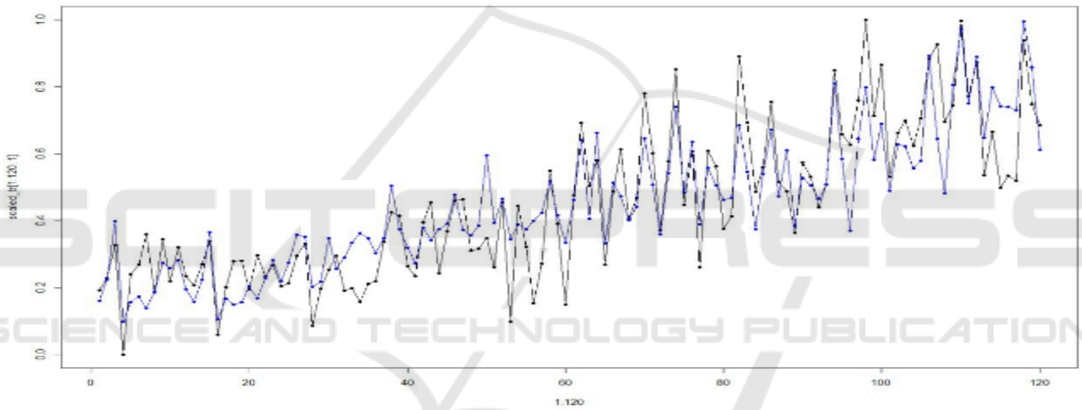

Figure 3: Calculated (black) and forecasted (blue) values of Y (GLM method).

A specific feature of the methodological approach to building a forecasting model is artificial neural networks` method, which allows to take into account a significant number of impact factors and to ensure minimal forecasting error (Kernasyuk, 2017), the nonlinearity and interaction of parameters (Maehashi, 2020). Analysis of the obtained models showed that the forecasting results based on the GLM method give the closest to the modelled values. Nevertheless, there are lower values of the RMSE metric (total error of the predicted value and known value) when teaching the model. This is because modelling of the most parameters` values for 2030 was based on the linear models of approximations. Thus, the GLM model was tracking the linear patterns of parameters behavior during training.

Table 2: Forecasting results by different methods.

Metrics	Forecasting methods		
	Neural net	Random forest	GLM
RMSE	24424,36	27835,16	27735,43
R^2	0,82862	0,77741	0,77901
Predict for 2030	465768	403835	483210
Modelled decision	508356	508356	508356
Forecast accuracy, %	91,62	79,44	95,05

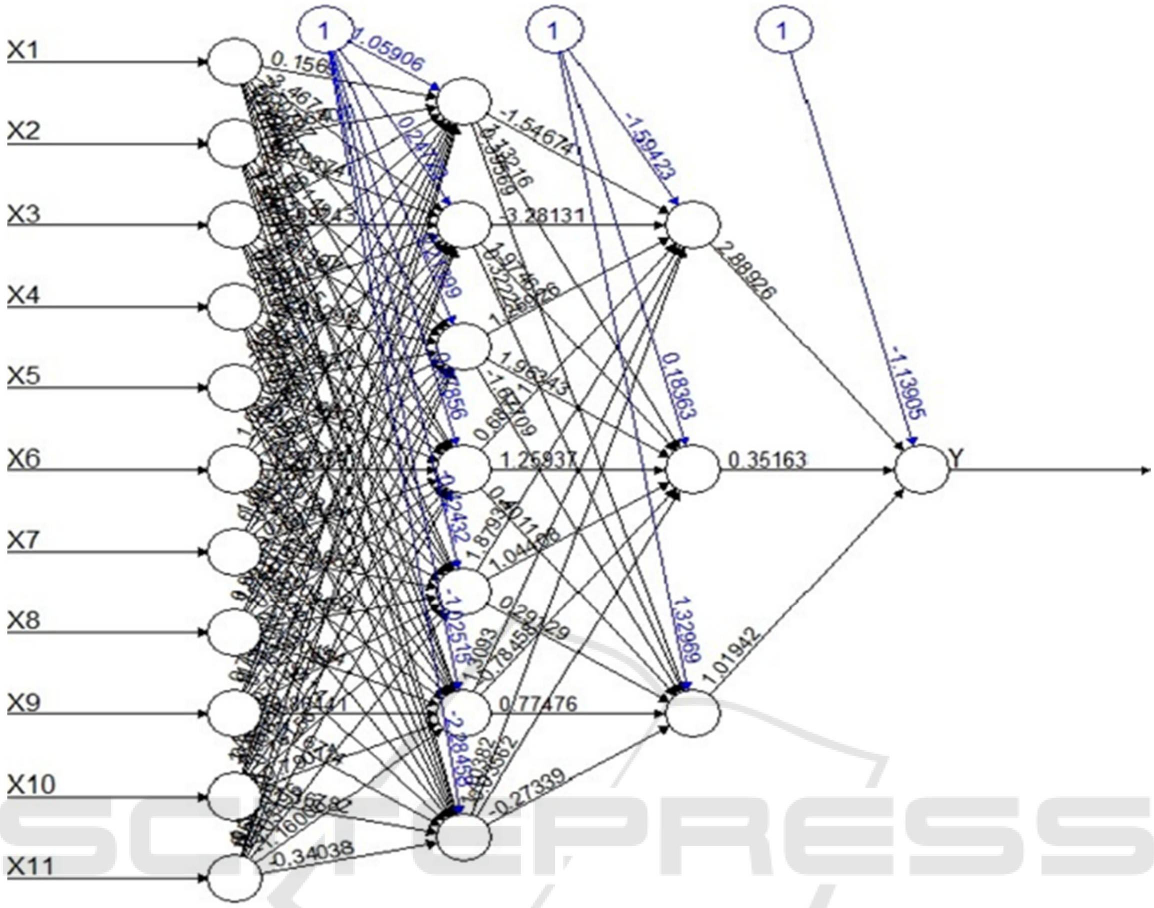

Figure 4: Adaptive neural model for forecasting sustainable development in the agrarian sector.

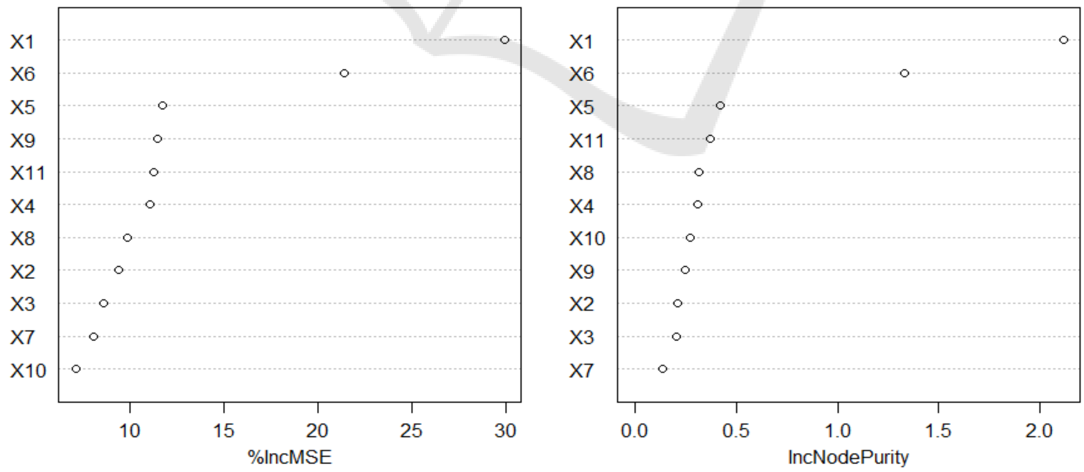

Figure 5: Each predictor`s importance.

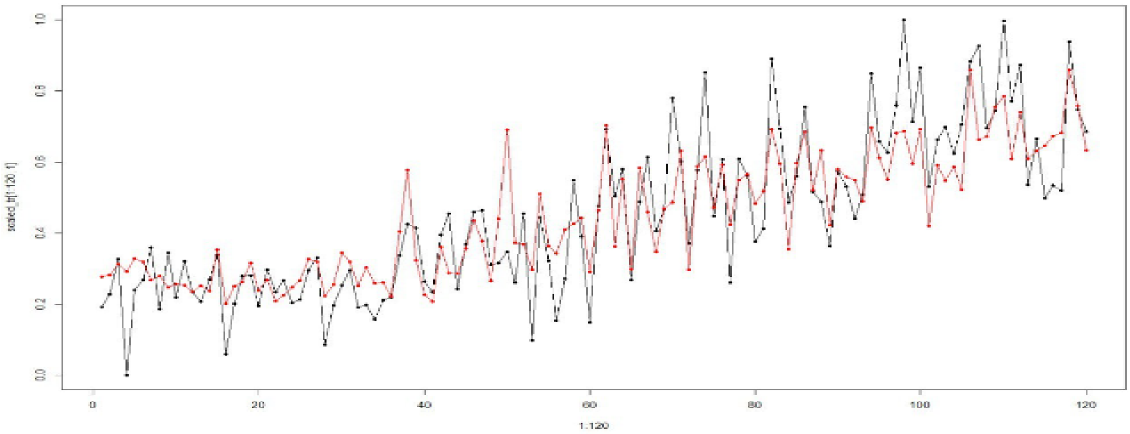

Figure 6: Calculated (black) and forecasted (red) values of Y (Random forest method).

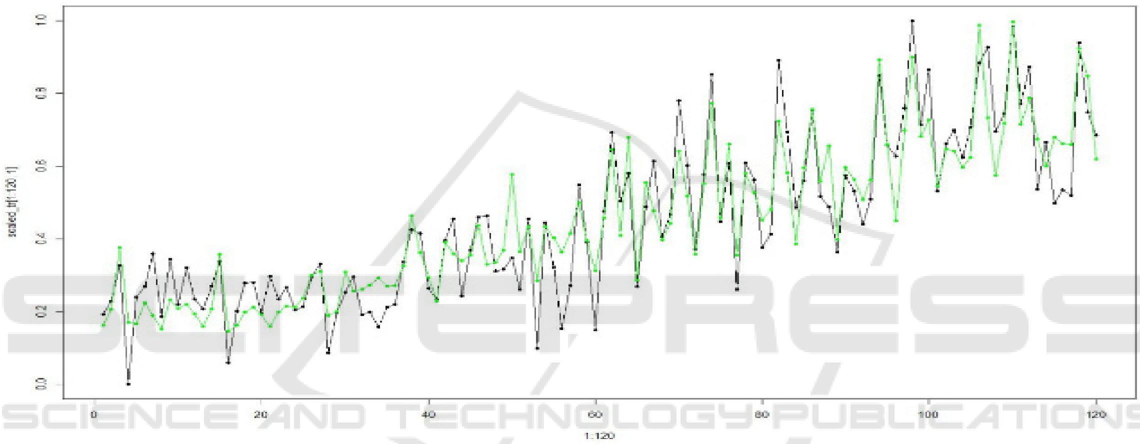

Figure 7: Calculated (black) and forecasted (green) values of Y (Artificial neural networks method).

However, the results based on the neural network give the lowest values of the RMSE metric. It means that the model studied as much as possible real hidden patterns of the analyzed data (necessary reliable information for forecasting), and was able to build a more reliable forecast. This is also proved by the coefficient of determination R^2 of the neural network model. It shows the degree of dispersion, being the highest in the neural network.

The results based on the Random forest model give much lower indices than in other models, therefore, its application in this type of data for this problem statement, in our opinion, cannot be considered appropriate.

When doing research, the emulated data obtained from the training data was applied for testing. Testing results were similar to the results based on the training data. In the future, for the accuracy of forecasting, it is interesting to perform tests based on real historical data. Their collection is somewhat complicated by the changed methodology and reporting documentation of the State Statistics Service of Ukraine.

Thus, based on the results, we can conclude that the built neural network model gives more reliable results for forecasting sustainable development parameters in agriculture and can be used to develop strategic management trends for labour potential in agriculture, which will ensure its future development.

4 CONCLUSIONS

The neural network modelling allows to form a multifactor impact model on the resulting indicator, namely labour productivity in accordance with sustainable development goals. The following impact factors have been identified in the model: the average monthly nominal wages of full-time employees in agriculture, UAH (X_1); energy security (power capacities/sown area), kW/100 ha (X_2); power-weight ratio (power capacities /number of employees), kw/per capita (X_3); number of tractors per 100 hectares of sown area (X_4); number of tractors per 1,000 employees (X_5); mineral fertilizers per 1 hectare of sown area, kg (nutrients) (X_6); organic fertilizers for agricultural crops, per 1 hectare of sown area, tons (X_7); stationary and mobile sources of air pollution, per capita, kg (X_8); total waste accumulated at landfill sites per capita, kg (X_9); average index of regional human development (X_{10}); capital investment per capita, UAH (X_{11}). X_1 (average monthly nominal wage), X_6 (mineral fertilizers), X_5 (number of tractors), and X_{11} (capital investment) have the most significant impact on the result. The proposed model allows modelling and forecasting, based not only on previously obtained indicators and their change dynamics (it is the studied period from 2008 to 2019), but to set targets, which is important in the context of sustainable development. That is why there is possibility to have administrative impact not only on the final result, but also on the process of achieving it, including optimization. In addition, the modelling allows to adjust impact factors, if they are either insignificant, as it has been found out when modelling, or lose significance due to technological changes (e.g. energy security and power-weight ratio). Thus, because of modelling aimed at forecasting the level of labour potential in the context of sustainable development, an approach to complex systems has been used. According to it, each of its components (impact factors on the resulting indicator) is also a systemic phenomenon. Modelling each factor`s behavior allows to affect their dynamics and effectiveness.

The advantages of the applied neural network modelling include the fact that there is no need to check (as in traditional modelling) multicollinearity, i.e. the linear relationship between factors. In the case they are detected, the factors are being eliminated. It devaluates the forecast. Therefore, the applied model takes into account all input parameters, based on their practical impact on the final result.

Thus, because of neural network modelling it is possible to identify strategic trends of labour potential management in the agricultural sector, as well as economic, social and environmental activities aimed at improving the quantitative and qualitative indicators of human capital.

The proposed model allows not only modelling and forecasting based on previously obtained indicators and the dynamics of their change, but also to set targets to obtain a range of possible scenarios for system development, depending on forecasting conditions and parameters, which not only increases the validity of managerial decision-making. It also ensures the relevance of management object`s adaptation to the ever-changing environment; managerial influence not only on the final result, but also on the process of its achievement, including the impact aimed at levers` of sustainable development optimization.

In further research when determining the strategic directions of labour potential management, it is advisable to use other models` parameters to characterize socio-environmental and economic aspects, considering their significant effect on the achievement of sustainable development goals in the agricultural sector.

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