DOI: 10.37943/15TYEQ8191

Aigul Mimenbayeva
Master of Sciences, Senior Lecturer of Department of the Information Systems
aigulka79_79@mail.ru, orcid.org/0000-0003-4652-470X
S.Seifullin Kazakh Agrotechnical Research University, Kazakstan

Anargul Shaushenova
Candidate of Technical Sciences, Head of the Department of Information Systems
a.shaushenova@kazatu.edu.kz, orcid.org/0000-0002-3164-3688
S. Seifullin Kazakh Agrotechnical Research University, Kazakstan

Sandugash Bekenova
Master of Sciences in Engineering, Lecturer of Higher School of Information Technologies
sandu79@mail.ru, orcid.org/0000-0001-7707-5623
West Kazakhstan Agrarian Technical University named after Zhangir Khan, Kazakstan

Maral Ongarbayeva
Candidate of Pedagogical Sciences, Head of the Department of Information and Communication Technologies
ongarbaevam@mail.ru, orcid.org/0000-0001-5258-7243
International Taraz innovative Institute named after Sherkhan Murtaza, Kazakstan

Lyazzat Zhumalieva
PhD, Acting Associate Professor of the Department of Mathematics in education
M.Kh. Dulaty Regional University, Taraz, Kazakhstan
lzdmath@mail.ru, orcid.org/0000-0002-1353-2677
Taraz Regional University named after M.Kh.Dulaty, Kazakstan

Zhanar Altynbekova
Doctoral student of Department of Informatics
altynbekova.zhanar1@mail.ru, orcid.org/0000-0001-5258-7243
Kazakh National Women’s Teacher Training University, Kazakstan

Ardak Nurpeisova
PhD, Senior Lecturer of the Department of Information Systems
a.nurpeisova@kazatu.edu.kz, orcid.org/0000-0002-1245-8313
S. Seifullin Kazakh Agrotechnical Research University, Kazakstan

NEURAL NETWORK MODEL OF SOIL MOISTURE FORECAST NORTH KAZAKHSTAN REGION

Abstract: Dealing with agriculture, it is valuable to know an amount of moisture in a soil and to know how to forecast the stored soil moisture within particular period. Forecasting the stored soil moisture works for planning an extent and structure of crop production areas and adjustment of plant-growing programs. Having known about an amount of moisture in one-meter soil and the depth of precipitation in a vegetation season shall help farmers to determine a seeding time, type of fertilizers depending on soil quality and to work out an irrigation schedule as well. In this regard, over the last few years some vigorous activities applied to machine training methods of the weather forecast have been launched in the world. The goal of present research is to develop an artificial neuron network which shall afford an op-

Received: 21.07.2023 Accepted: 13.09.2023 Published: 30.09.2023

portunity to figure out a stored soil moisture prior to outgoing to winter in a short-term. North Kazakhstan Region agrometeorological measuring stations for the period from 2012 to 2022 were used in the course of the neuron network training. The Levenberg-Marquardt algorithm aimed at non-linear regression models optimization was chosen for network training. The algorithm includes sequential approximation of initial parameter values to a local optimum. The mean squared error (MSE) function and the correlation coefficient ensure accuracy and precision of forecasts. As a result, 7 neural networks under MATLAB environment using the Levenberg-Marquardt algorithm, with different input and output data, and with different number of learning iterations came to realization. Following analysis of the results, the choice was fallen on the ANN9 best network offering minimum error function and actual data maximum correlation. The neural network obtained fits for use to make efficient decisions in the North Kazakhstan region agricultural sector in the short term.

Keywords: Neural network model; Levenberg-Marquardt; soil moisture; irrigation automation; forecasting; machine learning.

Introduction

Agricultural sector is one of key directions in the economy of our country and for the North Kazakhstan region as well. Total area of the North Kazakhstan region lands intended for agriculture covers 74% of the territory of the region including 4.9 million hectares of the arable lands and 2 million hectares of pastures.

The area specifies with sharp continental climate, fallouts of precipitations at the average 340-360 mm per year, amongst it 80% falls in warm season [1]. In this view the North Kazakhstan farmers encounter such problems as unequal distribution of precipitation during growing season, heighten temperature regime in summertime and scarcity of rainfalls nourishing winter crops at the seedling stage or in springtime. Conduction of a quality analysis and the region soil moisture forecast enable farmers to leverage irrigation schedules, crops water consumption, to figure out a profitability and volume of fertilizers applied which consequently shall provide an opportunity to increase crop yields in the North Kazakhstan region.

Soil moisture is a measure of the percentage of water contained in the soil. Absolute soil moisture is determined by the following formula (1):

$$W = \frac{m_a - m_b}{m_b} \cdot 100\%, \tag{1}$$

where m_a – mass of wet soil sample, m_b – mass of dry soil sample.

Soil moisture plays an important role in agriculture, especially in arid climates during the growing season of crops [2]. Insufficient soil moisture negatively affects the development and growth of agricultural crops [3-5].

Literature review

Domestic and foreign authors have performed much research aimed to problems concerning analysis and forecast of the soil moisture. Study of earth remote probing data such as vegetation indexes, meteorological data for the purpose to forecasting the soil moisture have found description in the labors [6]. This study has noted that the most promising method for predicting soil moisture content is balance calculations based on long-term meteorological data. It can also be noted that with the help of machine learning methods, acceptable skills of forecasting hydro meteorological variables, such as precipitation, drought, river runoff, soil moisture, have been demonstrated [7].

In the study [8], a regional system for maintenance of irrigation schedules under drought conditions using neural networks was created. In this work, daily values of air temperature, precipitation and vapor pressure deficit were designated as input parameters. Using these parameters, which were fed into a recurrent neural network, soil volumetric moisture was predicted three days ahead. The authors of [9] noted that for determining moisture retention, soil hydraulic properties are important parameters. To create simulation models, these parameters were obtained using the inverse modelling procedure and were adjusted using the least squares method and the Levenberg-Marquardt algorithm.

Rakesh et al. [10] comprehensively analysed the applicability of machine learning methods in seasonal climate prediction models. They noted that seasonal forecasts of soil moisture availability on a large scale are best made by combining climate prediction models with hydrological models.

Additionally, there are several machine learning algorithms such as, classification and regression trees (ART), Random Forest Regression (RFR) [11], support vector regression (SVR) [12], multiple linear regression modeling, boosted regression tree (BRT), artificial neural networks (ANN) [13] are used to predict soil moisture availability (Figure 1).

It is worth noting that the capabilities of many advanced machine learning techniques for data processing, with the exception of the use of neural networks, have not yet been fully explored [14].

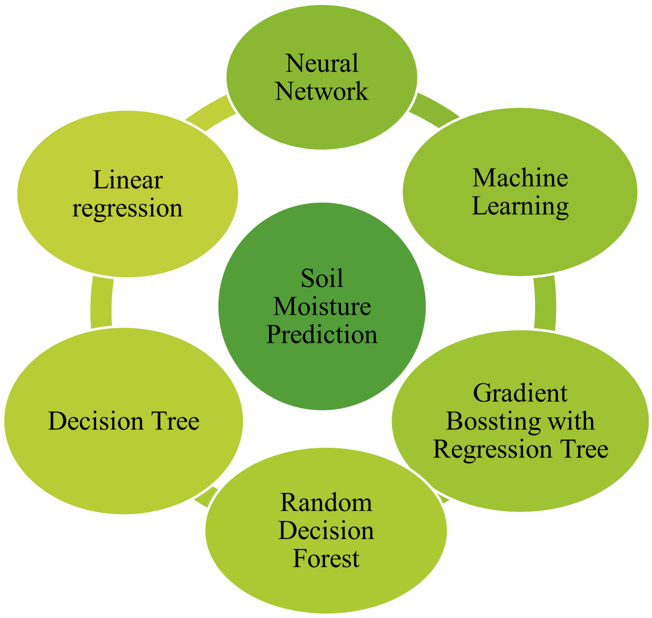

Figure 1. Soil moisture prediction methods

It is noted that the Random Forest method with minimal error showed a good result among the above methods.

The labor [15] has performed verification of multiple linear regression, recurrent neural networks, and support vectors for the purpose to estimate soil moisture. By a process of these methods' application to data sets, the multiple regression method provided a fair prediction with a minimum standard error and a high coefficient of determination.

The labor [16] by author A.Uthayakumar has used microwave short-range and broadband radars to measure soil moisture. The obtained data was processed using machine learning methods, such as neural networks, linear regression and the nearest k-neighbor method using KNN, SVM models. After a comparative analysis, the authors came to conclusion that the linear regression method, as in the previous labor, showed the best results with the maximum coefficient of determination [17]. Although, it was noted that under training using the MATLAB platform, the neural network model provides best results, with a fair estimate of adequacy

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 15, SEPTEMBER 2023

and values very close to real. In [18], an improved model structure based on advanced machine learning techniques was developed, which led to accurate identification of soil pollution sources. It is noted that, while most current research in this area has relatively small samples, the advantage of this study is the use of Vis-NIR technology to predict soil features, estimate errors in machine learning models from a large set of highly differentiated data and use them in soil and land assessment. In [19], two nonlinear regression models: multilayer perceptron (MLP) and support vector regression (SVR) are implemented to predict moisture content from newly acquired images.

The study [20] observed the greatest benefit of using the Levenberg-Marquardt algorithm with the help of tests in which large networks accompanied by long training samples are used. In this study, the training time is significantly reduced due to the smaller size of the Jacobian matrix in the implementation of the algorithm.

The authors of [21] noted that the hydraulic properties of the soil are important parameters for determining moisture retention. To create simulation models, these parameters were obtained using the reverse modeling procedure and were adjusted using the least squares method and the Levenberg-Marquard algorithm.

Thus, the prediction of agrometeorological factors using artificial neural networks (INS) has widely attracted the attention of researchers.

Purpose and Objectives of Research

The goal of present research is to train an artificial neural network to help to predict the stored soil moisture in one-meter layer of soil prior to outgoing to winter in the North Kazakhstan region in the short term.

The object of the research is the temporal sequences of data of the stored soil moisture prior to outgoing to winter in the North Kazakhstan region (2012-2022).

In order to achieve the goal, the following tasks were set:

- prepare an appropriate data set on the moisture availability in the North Kazakhstan region per individual meteorological stations within 2012-2022;
- build neural nets with different characteristics of features and using the Leven-berg-Marquardt algorithm;
- compare graphs of losses, learning rates, accuracy and correlation coefficients with the actual data of all trained neural networks;
- choose the best network for which the error function reaches a local optimum.

The Levenberg-Marquardt algorithm

This is the most common method designated to optimization of parameters of non-linear regression models. When this algorithm is executed, the initial values of the parameters consistently approach to a desired local optimal value [21].

Let a set of pairs of $u \in U^M$ free variables, $v \in V^M$ dependent variables and a functional relationship between these variables, which is a regression model $v = f(w, u_n)$. Let this function be continuously differentiable in the WU domain. It is required to find the value of the vector of weight coefficients w at which the error function

$$E_p = \sum_{k=1}^{N} (v_n - f(w, u_n))^2, \tag{2}$$

reaches a local minimum.

Before starting this algorithm, $w = [w_1, ..., w_R]^T$ a vector of weighting coefficients and a small value parameter are set $\mu \geq 0$.

1. When performing each step of the algorithm, the specified vector w is replaced b $w = w + \Delta w$.

2. $f(w+\Delta w, u) \approx f(w,u) + J\Delta w$

$$J = \begin{bmatrix} \frac{df(w,u_1)}{dw_1} \dots \frac{df(w,u_1)}{dw_R} \\ \dots \quad \dots \quad \dots \\ \frac{df(w,u_N)}{dw_1} \dots \frac{df(w,u_N)}{dw_R} \end{bmatrix}, \tag{3}$$

J is the Jacobian of the function $f(w, u_n)$ at a given point of the weights w. The increment of the argument Δw at the point w that delivers the minimum value E_p to the error function is zero. Therefore, to find the following increment values, the value of the vector of the partial derivative was equated to zero:

$$\frac{dE_D}{dw} = (J^T J)\Delta w - J^T(v - f(\omega)) = 0\,. \tag{4}$$

Thus, in order to find the value of the vector of weighting coefficients w, at which the error function reaches a local optimum, it is necessary to solve the following system of equations:

$$\Delta w = (J^T J)\Delta w - J^T(v - f(\omega))\,. \tag{5}$$

Further, for each iteration of the algorithm, a parameter is assigned

$$\Delta W(J,\mu) = (J^T J + \mu I)^{-1} J^T (v - f(\omega)), \tag{6}$$

where I is the unit matrix.

Figure 2 shows a flowchart of the implementation of the Levenberg-Marquardt algorithm on the MATLAB platform.

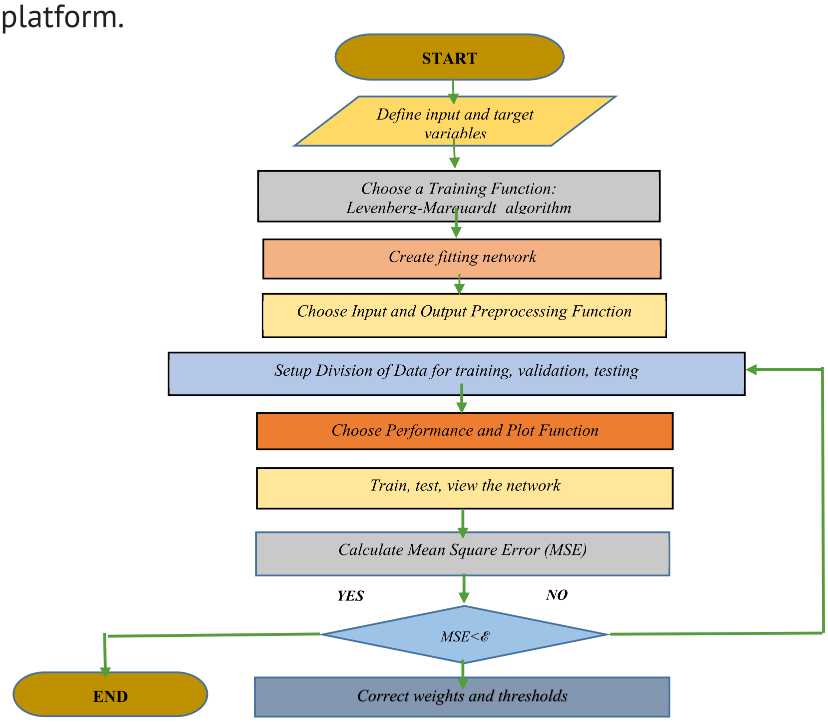

Figure 2. The flowchart of the Levenberg-Marqwart algorithm on the Matlab platform

The data on the amount of moisture in the soil before going into winter for 2012-2022 in the districts of North-Kazakhstan region (Table 1) are fed to the input of the network.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 15, SEPTEMBER 2023

To implement the algorithm according to the given flowchart (Figure 2), temperature (T_{vp}) and atmospheric humidity, humidity (H_{vp}), soil moisture (S_{sm}) during the growing season of crops were selected as features. The result of the neural network will be the predicted value of soil moisture for the next 3 years.

Table 1. Data on soil moisture availability in the North-Kazakhstan region for 2012-2022

№	Years	Tvp, 0C	Hvp, %	Ssm, mm
1	2012-2013	18	48	43
2	2013-2014	18	62	56
3	2014-2015	18,5	68	69,4
4	2015-2016	19,3	75	42
5	2016-2017	19,2	56	68
6	2017-2018	18,2	49	218
7	2018-2019	18,1	66	43
8	2019-2020	19,1	58	160
9	2020-2021	19,5	90	68
10	2021-2022	19,3	66	68

Experimental analysis and discussion

In framework of this article, implementation of a neural net training in the MATLAB package Neural Network Toolbox environment that consists of three layers: input (n neurons), hidden (m neurons) and output (p neurons) was observed. This sample of Table 1 was divided into three parts: training, control and test. The training part is designed to build a neural network model - the relationship between the amount of moisture before winter and the amount of moisture in the snow. The control sample is applicable for current assessment of the quality of training and makes it possible to prevent the retraining of the neural network.

Figure 3 shows the implementation code according to the block diagram above. Using the Levenberg-Marquardt algorithm, the procedures of training, testing and implementation of the neural network model with different number of hidden neurons were carried out in MATLAB platform. To train the neural network, a training sample was formed, consisting of: training data-70%, validation data-15%, test data-15%. Neural networks with different inputs and outputs, 30, 20, 10 hidden neurons were used for experimental training. A total of 7 different training samples were generated. The Mean Squared Error (MSE) function was chosen as the evaluation function. According to a given block diagram, after the training and testing procedure, the value of the MSE function is estimated. When MSE<E there is an adequate model, otherwise, it's needed to set up the model again, reselecting the number of hidden neurons, the number of test and training data.

The test results of the neural network trained on each of the given training samples are summarized in Table 2.

Table 2. Results of training the neural network using the Levenberg-Marquardt algorithm

Number of observations	Training data	Test data	Validation data	Number of hidden layers	Obser-vations	Mean Square Error (MSE)	R
ANN1	70	10	20	10	7	12.64	0.05
ANN2	70	10	20	30	7	0.13	0.99
ANN3	70	20	10	10	7	0.838	0.80
ANN4	70	20	10	20	7	1.75	0.41
ANN5	70	15	15	20	6	31.51	0.14
ANN6	70	20	10	10	7	0.008	0.999

DOI: 10.37943/15TYEQ8191

Analyzing the results of network training, it is seen that the ANN6 network obtained the best results with the lowest error functions MSE=0.008 and the best correlation of training 0.999 with the actual data of moisture reserves.

Figure 3 shows a code fragment of the implementation of the Levenberg-Marquardt algorithm, according to the flowchart shown in Figure 2.

```
untitled * × | Moisture reserve4.xlsx × | +

%   Define input and target variables for Neural Network Model of Soil
%   Moisture Forecast North Kazakstan Region

%   Input_data1 - input data.
%   Output_data1 - target data.

x = Input_data1';
t = Output_data1';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.

% Create a Fitting Network
hiddenLayerSize = 20;
net = fitnet(hiddenLayerSize,trainFcn);

% Choose Input and Output Pre/Post-Processing Functions
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};
```

```
untitled * × | Moisture reserve4.xlsx × | +

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
    'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y);

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y);
valPerformance = perform(net,valTargets,y);
testPerformance = perform(net,testTargets,y);

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
    % Generate MATLAB function for neural network for application
    % deployment in MATLAB scripts or with MATLAB Compiler and Builder
```

Figure 3. Code for implementing the task in the MATLAB platform

Next, let us consider the ANN6 network training process in detail. The following table shows the technical characteristics of the neural network training result for predicting soil moisture (Table 3). Here Epoch is the number of iterations, epochs; Performance is the value of the root–mean–square error function; Gradient is the gradient value; μ is the value of a small value entered into the algorithm to update the weights.

Table 3. Training results: Met validation criterion

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	3	1000
Performance	11.2	3.17e-20	0
Gradient	36.5	5.42e-10	1e-07
Mu (μ)	0.001	1e-06	1e+10
Validation Checks	0	2	6

The two-layer feedforward network with sigmoid hidden neurons and linear output neurons for regression tasks illustrated in figure 3:

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 15, SEPTEMBER 2023

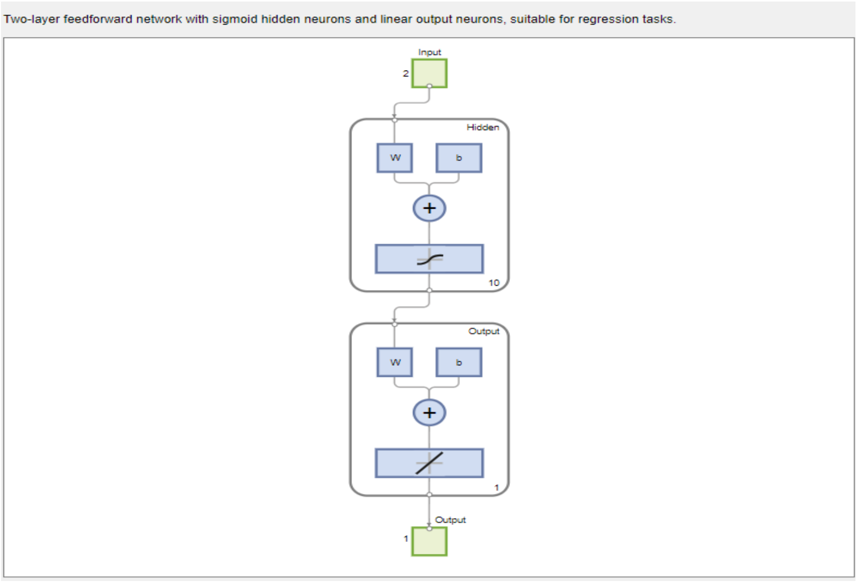

Figure 3. Two-layer feedforward network with sigmoid hidden neurons and linear output neurons

According to the values in the table it is clear that on the 5th iteration the local minimum of the error function has been reached, with learning quality Performance=3.17e-20, at which the created neural network optimally predicts soil moisture according to the previous values. In the test sample the quality of prediction is checked, in the considered network the optimal quality is achieved at the 3th test sample.

Next, let's look at the graph of the error function (Figure 4).

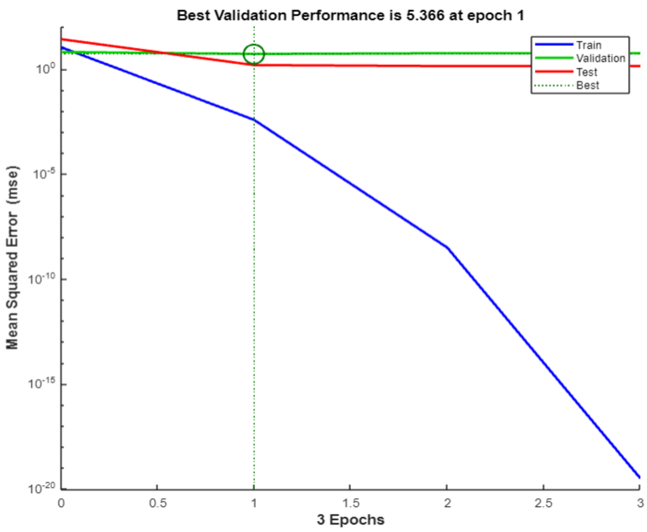

Figure 4: Mean square error plot

The diagram of errors shows dependence of the number of correctly predicted objects on training iterations, therefore an area under the test curve reflects the proportion of objects correctly predicted by the neural network using the Levenberg-Marquart algorithm. Figure 4 illustrates the diagram of the root-mean-square error function, which shows that the value of the error function decreases with each epoch. Training stops when the error on the validation data set stops decreasing. Carrying out of analysis of the correlation dependencies between the input data of moisture availability reserves and target values also had place (figure 5).

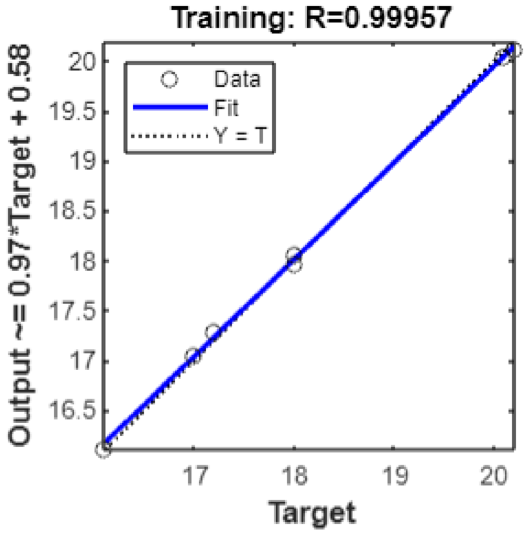

Figure 5. Results of correlation analysis

The diagram of correlations shows the network's predictions (outcoming data) on the training, validation, and test data sets. The best correlation R=0.99 was obtained with the value of the output parameter value Output=0,97*target+0,58. Hereof seems to conclude that a high correlation coefficient, along with an error function fits for usage as a criterion for neural network prediction.

Table 4. Values of actual and predicted soil moisture reserves

Years	Actual values of soil moisture, mm	Predicted values of soil moisture, mm	Deviations of actual soil moisture from predicted
2012-2013	43	42,9	0,012
2013-2014	56	55,8	0,192
2014-2015	64,4	63,71	0,680
2015-2016	42	40,8	1,192
2016-2017	68	68,7	-0,707
2017-2018	218	219,65	-1,651
2018-2019	43	43,11	-0,119
2019-2020	160	161,02	-1,026
2020-2021	68	66,55	1,448
2021-2022	69	70,57	-1,574
2022-2023	72	71, 28	0, 724
2023-2024	-	61, 46	-
2024-2025	-	55, 29	-
2025-2026	-	66, 34	-

The absolute error is calculate according to the following formula (2):

$$\mathcal{E} = \sum_{k=1}^{n} \left| \frac{C_k^{Pred} - C_k^{Fact}}{n} \right| = 0{,}013 \tag{2}$$

The absolute error is closer to 0, which indicates the high accuracy of the resulting ANN7 network.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 15, SEPTEMBER 2023

Conclusion

To predict the moisture content of the soil of the North Kazakhstan region, a neural network was created based on a double-layer perceptron. Data on the stored soil moisture within 2012-2022 were submitted to the input. A neural network based on a two-layer perceptron was created to predict soil moisture content in the North Kazakhstan region. Moisture concentration in the soil depends on the level of precipitation, intensity of vegetation absorption, air temperature and other factors. Therefore, the data on temperature and atmospheric humidity, which can characterize the accumulated soil moisture for the period 2012-2022, were fed to the input.

1. An array consisting of archived data on moisture reserve, temperature quantity, humidity during the growing season of the North-Kazakhstan region for 2012-2022 was prepared.

2. Procedures of training, testing and realization of neural network model with different number of hidden neurons were carried out. The neural network was built with data consisting of 70% training data with different inputs and outputs, consisting of 30, 20, 10 hidden neurons. A total of 7 different training samples were created.

3. In the training process, the best ANN6 network was selected, with the lowest error function MSE=0.008 and the best training correlation of 0.999. At the same time, the error function reached its minimum value, and the correlation coefficient showed a fairly close relationship between the predicted and actual data. Table 4 shows actual and forecast values of moisture reserve of North-Kazakhstan region obtained using ANN6 network and forecast for the next 3 years. The value of absolute error is equal to E=0.013, which shows good quality of the created neural network model.

It should be noted that in the process of training, reducing the number of iterations using the Levenberg-Marquardt algorithm and increasing the number of test data led to an increase in the accuracy and performance of the model for forecasting moisture reserves.

Creation of the neural network model to predicting crop yields in the North Kazakhstan region shall forward further research in this area. Additionally, plans to realize the model using advanced architecture to improve the accuracy of its function are underway.

References

[1] Babkenova, S., Abdullayev, K., & Kairzhanov, Y. (2020). Breeding Spring Soft Wheat for Productivity, Grain Quality, and Resistance to Adverse External Factors in Nothern Kazakhstan. *Journal of Ecological Engineering*, 21(6), 8- 12. https://doi.org/10.12911/22998993/123160

[2] De Natale, F., Alilla, R., Parisse, B., & Nardi, P. (2023). A bibliometric analysis on drought and heat indices in agriculture. *Agricultural and Forest Meteorology*, 341, 109626, https://doi.org/10.1016/j.agrformet.2023.109626.

[3] Ahmad, N., Malagoli, M., Wirtz, M., & Hell, R. (2016). Drought stress in maize causes differential acclimation responses of glutathione and sulfur metabolism in leaves and roots. *BMC Plant Biology,* 16(1), 247. https://bmcplantbiol.biomedcentral.com/articles/10.1186/s12870-016-0940-z

[4] Acharya, U., Daigh, A., & Oduor, P. (2021). Machine Learning for Predicting Field Soil Moisture Using Soil, Crop, and Nearby Weather Station Data in the Red River Valley of the North. Soil Systems, 5, 57. https://doi.org/10.3390/soilsystems5040057

[5] Brinkhoff, J., Hornbuckle, J., & Ballester, L. (2019). Soil moisture forecasting for irrigation recommendation. *Proceedings of 6th IFAC Conference on Sensing, Control and Automation Technologies for Agriculture Agricontrol*, 52 (30), 385-390. https://doi.org/10.1016/j.ifacol. 2019.12.586

[6] Barrera-Animas, A., Oyedele, L., Bilal, M., Akinosho, T., Delgado, J., & Akanbi, L. (2022). Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting. *Machine Learning with Applications*, 7, 100204. https://doi.org/10.1016/ j.mlwa.2021.100204.

[7] Filipović, N., Brdar, S., Mimić, G., Marko, O., & Crnojević, V. (2022). Regional soil moisture prediction system based on Long Short-Term Memory network. *Biosystems Engineering*, 213, 30. http://dx.doi.org/10.1016/j.biosystemseng.2021.11.019

[8] Zhiming, C., Mingyang, W., Yinuo, S., Xu, X., Wenhan, Y., Chuanxin, Y., & Tianxiang, H. (2022). Predicting stress-dependent gas permeability of cement mortar with different relative moisture contents based on hybrid ensemble artificial intelligence algorithms. Construction and Building Materials, 348, 128660. https://doi.org/10.1016/j.conbuildmat.2022.128660

[9] Rakesh, C., Dongryeol, R., Patrick, N., Lane, J., & Gary, J. (2023). Seasonal forecast of soil moisture over Mediterranean-climate forest catchments using a machine learning approach. Journal of Hydrology, 619, 129307. https://doi.org/10.1016/j.jhydrol.2023.129307

[10] Sun, Z.,Wang, G., Li, P., Wang, H., Zhang, M., & Liang, X. (2023). An improved random forest based on the classification accuracy and correlation measurement of decision trees. Expert Systems with Applications, 237, 121549. https://doi.org/10.1016/j.eswa.2023.121549

[11] Jin, J., Verbeurgt, J., Sloover, L., Stal, C., Deruyter, G., Montreuil, A., Vos, S., De Maeyer, P., & De Wulf, A. (2021). Support vector regression for high-resolution beach surface moisture estimation from terrestrial LiDAR intensity data. International Journal of Applied Earth Observation and Geoinformation, 102, 102458. https://doi.org/10.1016/j.jag.2021.102458

[12] Wang, S., Li, R., Wu, Y., & Wang, W. (2023) Estimation of surface soil moisture by combining a structural equation model and an artificial neural network (SEM-ANN). Science of The Total Environment, 876, 162558. https://doi.org/10.1016/j.scitotenv.2023.162558

[13] Prakash, S., Sharma, A., & Sahu, S. (2018). Soil Moisture Prediction Using Machine Learning. Proceeding of Second International Conference on Inventive Communication and Computational Technologies, Coimbatore, India, 1-6. http://dx.doi.org/10.1109/ICICCT. 2018.8473260

[14] Uthayakumar, A., Mohan, M., Khoo, E., Jimeno, J., Siyal, M., & Karim, M.F. (2022). Machine Learning Models for Enhanced Estimation of Soil Moisture Using Wideband Radar Sensor. *Sensors*, 22, 5810. https://doi.org/10.3390/s22155810

[15] Acharya, U., Daigh, A., & Oduor, P. (2021). Machine Learning for Predicting Field Soil Moisture Using Soil, Crop, and Nearby Weather Station Data in the Red River Valley of the North. *Soil Systems*, 5, 57. https://doi.org/10.3390/soilsystems5040057

[16] Zheng, J., Wang, P., Shi, H., Zhuang, C., Deng, Y., Yang, X., Huang, F., & Xiao, R. (2023). Quantitative source apportionment and driver identification of soil heavy metals using advanced machine learning techniques. *Science of The Total Environment*, 873, 12023. https://doi.org/10.1016/j.scitotenv.2023.162371

[17] Hajjar, C., Esta, M. & Chamoun, Y.G. (2020). Machine learning methods for soil moisture prediction in vineyards using digital images. *Proceeding of ICESD 2020 11th International Conference on Environmental Science and Development*, 67, 02004. https://doi.org/10.1051/ e3sconf/202016702004

[18] Huang, X., Cao, H., & Jia, B. (2023). Optimization of Levenberg Marquardt Algorithm Applied to Nonlinear Systems. Processes, 11, 1794. https://doi.org/10.3390/pr11061794

[19] Jiyang, D., Ke, L., Jian, X., Shuangfeng, D., Rui, Zh., & Weiguo, P. (2018). Accelerated non-rigid image registration using improved Levenberg–Marquardt method. *Information Sciences*, 423, 66–79. https://doi.org/10.1016/j.ins.2017.09.059