ANN-Based Modeling of Electro-Impulse Soil Treatment Processes with Digital Twin Forecasting

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Abstract: Continuous use of agricultural crop fields to achieve high yields leads to a decrease in the amount of nutrients and beneficial trace elements in the soil. To replenish the lost nutrients and trace elements in a short period of time, chemical fertilizers are additionally applied. Chemical fertilizers react with moisture and other substances in the soil, forming solid compounds that plants cannot absorb. By treating the soil with electrical impulse discharges, chemical fertilizers are converted into a form that can be absorbed by plants. In this study, the effect of soil electro-impulse treatment parameters on the content of trace elements was modeled using artificial neural networks. Based on the initial experimental data, a data augmentation method was applied, and a multi-output regression model was developed using a multilayer perceptron architecture. To evaluate the stability of the model, the K-Fold cross-validation method was used, and the average values of the coefficient of determination and mean squared error were calculated. The obtained results showed that the model operates with high predictive accuracy and can support near-real-time forecasting within a Digital Twin-oriented monitoring framework. The research results can be used to optimize electro-pulse technologies, automate agro-technological processes, and develop intelligent monitoring systems.

1 INTRODUCTION

Modern electrotechnological processes are increasingly applied in agriculture to improve resource efficiency, automate technological operations, and modify biological or physicochemical processes through controlled electrical effects [1]. Related research on electrically influenced process dynamics and electrical treatment technologies has demonstrated the importance of accurately representing the interaction between electrical parameters and the treated environment [2], [3]. In agricultural applications, the response of biological and soil-related systems may depend on multiple interacting physical and chemical factors, which creates a complex modelling problem.

The digitalization of technological processes has increased the demand for analytical and decision-support systems capable of processing heterogeneous process data and converting them into operational information [4]. Artificial intelligence provides a general computational framework for learning complex relationships, forecasting system behaviour, and supporting automated decision-making [5]. In electro-impulse applications, previous studies have investigated the mechanisms of pulsed electrical discharge and the effects of electrical treatment on biological and agricultural systems [6]-[9]. However, the nonlinear relationships between electrical operating parameters and changes in soil chemical composition remain difficult to describe using only conventional deterministic or statistical approaches.

Machine-learning methods offer an alternative approach for predictive modelling of multidimensional technological data [10]. Artificial neural networks are particularly suitable for learning complex nonlinear dependencies and representing hidden relationships between multiple input and output variables [11]. For electro-impulse soil treatment, the simultaneous influence of voltage, energy density, and pulse duration on Nitrogen, Phosphorus, Potassium, Calcium, and Magnesium content can therefore be formulated as a multi-input, multi-output regression problem. A neural-network model can learn these relationships from experimental observations and generate quantitative forecasts for previously unseen combinations of process parameters.

The Digital Twin concept further extends predictive modelling by linking a virtual computational representation with the operating state of a physical process. Contemporary Digital Twin research emphasizes continuous data integration, cognitive modelling, and model-supported decision-making in complex cyber-physical environments [12]-[15]. Human-centric and intelligent Digital Twin architectures also demonstrate the growing importance of adaptive analytical models and structured interaction between physical data, predictive components, and operational decisions [16], [17]. Within an electrotechnological process, such an approach can transform an offline neural-network model into a virtual predictive component capable of receiving process variables, estimating soil chemical responses, and supporting parameter adjustment.

Despite progress in artificial intelligence and Digital Twin technologies, limited attention has been given to their combined application for modelling the effect of electro-impulse soil treatment parameters on multiple soil chemical indicators. In particular, there is a need for reproducible multi-output prediction models that account for limited experimental datasets, evaluate generalization through cross-validation, and provide a computational basis for future real-time process monitoring.

The aim of this study is to develop and evaluate an artificial neural network-based multi-output regression model for predicting changes in soil microelement content under different electro-impulse treatment conditions and to integrate the trained model into a Digital Twin-oriented forecasting workflow. The proposed approach combines experimental data, training-set augmentation, multilayer perceptron modelling, K-Fold cross-validation, comparative baseline evaluation, and model-based process forecasting. The main contribution of the study is a closed data-model-decision framework that links electro-impulse operating parameters with predicted soil chemical responses and provides an analytical basis for intelligent monitoring and process optimization.

2 METHODOLOGY

In this study, the electro-impulse treatment process is considered as a multi-input, multi-output nonlinear regression problem. The mathematical model of the process is based on an artificial neural network that represents the nonlinear relationship between the input process parameters and the output element concentrations [10], [11].

Based on experimental data, the input parameter vector is determined as follows:

$$x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} U \\ E \\ t \end{pmatrix}, \tag{1}$$

where U is the voltage, E is the energy density, and t is the pulse duration.

The output parameter vector is defined as follows:

$$y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{pmatrix} = \begin{pmatrix} N \\ P \\ K \\ Ca \\ Mg \end{pmatrix}. \tag{2}$$

The nonlinear modelling task is expressed as follows:

$$y = f(x; \theta). \tag{3}$$

There: f — nonlinear functional relationship, θ — vector of model parameters.

Standardization was applied to each input and output variable to ensure numerically consistent model training [10]:

$$\hat{x}_i = \frac{x_i - \mu_x}{\sigma_x},\ \hat{y}_j = \frac{y_j - \mu_y}{\sigma_y}. \tag{4}$$

There μ— average value, σ — standard deviation. Neural network L consists of layers, and the following connection is valid for each layer:

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)},\ a^{(l)} = \varphi\left(z^{(l)}\right). \tag{5}$$

Where:

- $W^{(l)}$— weight matrix,
- $b^{(l)}$ — displacement vector,
- $\varphi(\cdot)$— activation function.

The ReLU function is used in the hidden layers:$\varphi(z) = \max(0, z)$.

Linear activation is used in the output layer:$a^{(L)} = z^{(L)}$.

The resulting forecast value is:$\hat{y} = f(\hat{x}; \theta)$.

The model was trained by minimizing the mean squared error loss function [10].

The model parameters are determined based on the mean square error criterion:

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left\|\hat{y}^{(i)} - y^{(i)}\right\|^2, \quad (6)$$

For the multi-output regression problem, the loss can be expressed by components as follows:

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{5}(\hat{y}_{ij} - y_{ij})^2, \quad (7)$$

The model parameters were optimized using a gradient-based learning procedure [10]:

$$\theta_{k+1} = \theta_k - \alpha\nabla_\theta J(\theta_k), \quad (8)$$

there α — learning speed.

Model performance was assessed using the coefficient of determination R^2 and prediction-error metrics [10]:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left\|y^{(i)} - \hat{y}^{(i)}\right\|^2}{\sum_{i=1}^{N}\left\|y^{(i)} - \bar{y}\right\|^2}, \quad (9)$$

There $\bar{y}$ — vector of average values.

The generalization stability of the model was evaluated using 5-fold cross-validation [10].

The sample is divided into *K* equal parts:

$$D = \bigcup_{k=1}^{K} D_k\,. \quad (10).$$

At each iteration, the model is trained on K−1 folds and evaluated on the remaining fold. The final cross-validation score is calculated as the mean of the fold-wise evaluation results [10]:

$$R^2_{avg} = \frac{1}{K}\sum_{k=1}^{K} R^2_k,\ MSE_{avg} = \frac{1}{K}\sum_{k=1}^{K} MSE_k\ .(11)$$

2.1 Digital Twin Model

The trained predictive model was subsequently incorporated into a Digital Twin-oriented workflow consistent with contemporary virtual-representation and model-supported decision concepts [12]-[17]:

$$DT(x_t) = f(x_t;\theta^*), \quad (12).$$

where θ^* — optimal parameters trained on all data.

For near-real-time operation, newly acquired process variables are standardized using the training-set statistics and supplied to the trained model to generate updated estimates of the output chemical indicators.

In this study, a multilayer perceptron-based artificial neural network model was used to solve the multi-output regression problem. The model architecture consists of three hidden layers, with the number of neurons in them being 128, 64, and 32 units, respectively. The ReLU activation function was used in the hidden layers, and the linear activation function was used in the output layer, since the output variables are continuous quantitative indicators. The mean square error (MSE) was chosen as the loss function. Optimization was performed based on the Adam algorithm, with an initial learning rate of 0.001. The training process was performed for 300 epochs with a mini-batch size of 16. In order to reduce overfitting, a dropout mechanism with a coefficient of 0.2 and L2-regularization ($\lambda = 10^{-4}$) were used. An early stopping mechanism based on the dynamics of the validation loss function was introduced.

Given the limited data size, a statistical data augmentation approach was used. In order to reliably assess the generalization ability of the model, a 5-fold cross-validation scheme was used. The data were randomly shuffled and divided into five non-intersecting partitions. In each iteration, four partitions were used as training and one as validation. The trained neural-network model was subsequently integrated into a Digital Twin-oriented workflow for predictive representation and model-supported monitoring of the electro-impulse treatment process [12]-[17].

2.2 Digital Twin Implementation Workflow

In this study, the Digital Twin is implemented as a virtual predictive representation of the electro-impulse treatment process, where the physical operating parameters are continuously mapped to a trained multi-output neural network model. The input layer of the twin receives the current process variables, namely voltage U, energy density E, and pulse duration t, which can be acquired either directly from the experimental setup or from a monitoring interface connected to the power supply and process control unit. The reliability of sensor-driven predictive systems also depends on measurement calibration, uncertainty evaluation, and the metrological stability of the data-acquisition chain [18]. Although the measured variables differ across engineering applications, these principles are relevant to Digital Twin systems because measurement bias in physical-process inputs may propagate into model forecasts. These inputs are standardized using the same statistics as in model training and are then fed into the trained MLP to estimate the current values of Nitrogen, Phosphorus, Potassium, Calcium, and Magnesium. Digital monitoring studies in distributed engineering environments have similarly demonstrated the value of transforming acquired observational data into structured analytical information for model-based monitoring [19]. In the present framework, this general data-integration principle is applied to electro-impulse process variables before neural-network inference. The predicted output vector is subsequently compared with the target operating range obtained from the experimental dataset. If the predicted values deviate from the desired agronomic interval, the Digital Twin can support corrective adjustment of the controllable input parameters U, E, and t. In this way, the proposed framework forms a closed data-model-decision loop and extends the model from offline forecasting to a practically applicable Digital Twin for process monitoring and parameter optimization. Data-driven management workflows have also demonstrated that heterogeneous quantitative indicators can be transformed into transparent decision priorities and structured operational actions [20]. Following a similar decision-support principle, the proposed Digital Twin converts physical input variables and predicted soil-response indicators into analytical information that can support process-parameter adjustment.

3 RESULTS

The predictive performance of the artificial neural network and its applicability within the proposed Digital Twin-oriented workflow were evaluated using cross-validation, variable-wise error metrics, comparative baseline models, and graphical analysis. The results show that the MLP model can represent nonlinear relationships between the electro-impulse input parameters and the predicted soil chemical indicators. The generated surface and trend plots additionally illustrate the influence of voltage and energy-related process conditions on the predicted element concentrations.

The experimental data set used in the study was collected to assess the chemical composition of the soil after electrophysical treatment. The experimental data consisted of a total of N = 180 observation points, each experiment was repeated three times and the average value was calculated. The soil element contents were reported in the units used in the experimental protocol. Nitrogen (N), Phosphorus (P), Potassium (K), Calcium (Ca), and Magnesium (Mg) were expressed in mg/100 g. The chemical elements in the soil samples were determined in the laboratory using standard agrochemical methods. The nitrogen content was determined using the Kjeldahl method, and the phosphorus and potassium contents were measured using spectrophotometric analysis. The calcium and magnesium concentrations were determined using atomic absorption spectrometry. The accuracy of the measuring instruments was ±0.5 mg/kg. The experimental data range is given in Table 1.

Table 1: Experimental data range.

Parameter	Minimum	Maximum	Average
Nitrogen (N), mg/100 g	446.3	538.8	483.8
Phosphorus (P), mg/100 g	1.82	2.03	1.93
Potassium (K), mg/100 g	10.5	11.1	10.79
Calcium (Ca), mg/100 g	814.1	919.0	831.6
Magnesium (Mg), mg/100 g	1318	1336	1329.1

Table 2: K-Fold Cross-Validation results.

Fold	R^2 (Determination coefficients)	MSE (Squared error)
1	0.972	2.85
2	0.975	2.90
3	0.974	2.88
4	0.976	2.91
5	0.972	2.94

In order to increase the size of the dataset and improve the generalization ability of the model, data augmentation was used. In this process, new synthetic samples were generated by adding small random noise to the existing experimental data. Augmentation was performed based on the following mathematical model:

$$x_a = x + \varepsilon, \tag{13}$$

where x denotes the original observation and ε is zero-mean Gaussian noise. The noise standard deviation was set to 3% of the standard deviation of the corresponding variable. Given the limited size of the experimental dataset, data augmentation was applied separately within each cross-validation training fold. After the 5-fold split, each training partition contained 144 real observations and the validation partition contained 36 unchanged observations. Four synthetic samples were generated for each training observation, producing 576 augmented records. Thus, each training fold contained 720 observations in total, while the 36 validation observations remained unmodified. This fold-wise augmentation strategy prevented information leakage between the training and validation subsets. The fold-wise validation results of the neural-network model are presented in Table 2.

Table 2 reports the fold-wise validation performance of the multi-output model at the global level, where the average R^2 and MSE summarize the overall predictive stability across all outputs during cross-validation. However, because the task is a multi-output regression problem with five target variables having different physical ranges, an additional variable-wise evaluation is required. For this reason, the final model performance is also reported separately for each output in Table 7 using R^2, RMSE, and MAE. This two-level evaluation strategy makes it possible to assess both the overall robustness of the model and the prediction error structure for each chemical element individually.
Average values (Fig. 1):

$$R^2_{\mathrm{avg}} = 0.974, \quad \mathrm{MSE}_{\mathrm{avg}} = 2.896.$$

The average R^2 value exceeded 0.97, indicating that the model captured a substantial proportion of the variance in the output variables. The comparatively low cross-validation MSE values further indicate stable predictive performance across the five folds.

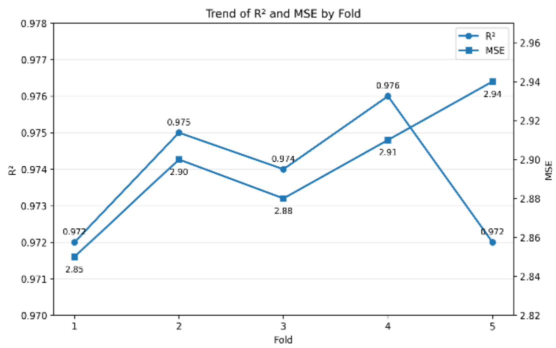

Figure 1: Trend of R² and MSE by Fold.

The Digital Twin Model Predictions are presented in Table 3.

Table 3: Digital twin model forecasts.

Element	Projected value	Actual range (experiment)
Nitrogen (N)	507.00	446 - 538
Phosphorus (P)	2.003	1.82 - 2.03
Potassium (K)	10.958	10.5 - 11.1
Calcium (Ca)	821.32	814 - 919
Magnesium (Mg)	1334.00	1318 - 1336

The predictions are in high agreement with the experimental values. The error for each element is minimal, and the reliability of the model is high (Fig. 2). Neural Network Model Predictions (All Data) are presented in Table 4.

The surface-based model allows for visual identification of subtle interactions between parameters (Fig. 2). The forecast of the Nitrogen element depending on the voltage parameter is presented in Figure 3. This study analyzed the effectiveness of predicting the amount of micronutrients (Nitrogen, Phosphorus, Potassium, Calcium and Magnesium) using the Digital Twin model based on artificial neural networks. Based on the results of K-Fold cross-validation, residual analysis, generated 3D graphics and Digital Twin trends, the following conclusions can be drawn [17].

As the voltage increases, the amount of Nitrogen increases, which demonstrates the effectiveness of the Digital Twin model in simulating physical processes. Data statistics are presented in Table 5, Digital Twin Results in Table 6.

Table 4: Neural network model predictions.

Row	Nitrogen (N, mg/100 g)	Phosphorus (P, mg/100 g)	Potassium (K, mg/100g)	Calcium (Ca, mg/100 g)	Magnesium (Mg, (mg/100 g)
1.	446.30	1.90	10.50	814.10	1320
2.	448.40	1.82	10.60	815.20	1318
3.	451.30	1.93	10.80	816.60	1324
4.	451.20	1.96	10.70	817.10	1331
5.	538.80	2.03	11.10	819.20	1336
6.	519.20	2.00	11.10	919.00	1335
7.	519.80	1.88	10.90	818.80	1336
8.	446.41	1.91	10.51	814.12	1320
9.	448.55	1.83	10.59	815.18	1318
10.	451.28	1.94	10.79	816.58	1324

Table 5: Data statistics.

Parameter	Min	Max	Mean	Std
Voltage-U, kV	0.0	9.0	5.43	2.83
Energy density E, J/m²	0.0	1100.0	671.4	362.8
Time-t, s	0.0	0.6	0.54	0.07
Nitrogen-N, mg/100 g	446.3	538.8	483.8	35.1
Phosphorus-P, mg/100g	1.82	2.03	1.93	0.07
Potassium-K, mg/100 g	10.5	11.1	10.79	0.19
Calcium-Ca, mg/100 g	814.1	919.0	831.6	37.9
Magnesium-Mg, mg/100g	1318	1336	1329.1	6.6

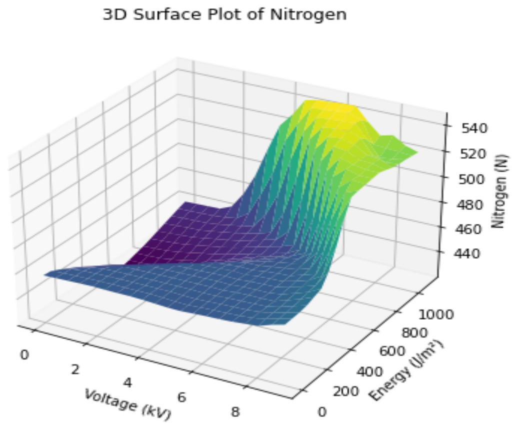

Figure 2: 3D Surface Plot - Nitrogen.

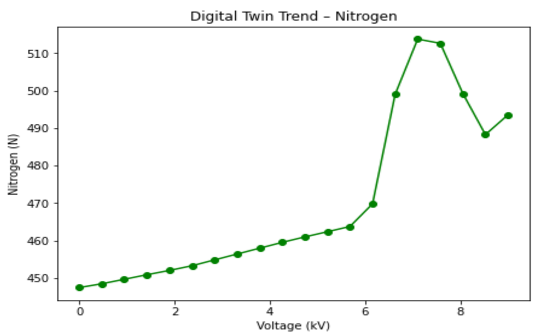

Figure 3: Forecast of the Nitrogen element depending on the voltage parameter.

From the Digital Twin perspective, the forecasts presented in Table 6 represent the current virtual state of the electro-impulse treatment process under the given operating conditions. In practical application, such predictions can be generated whenever new values of voltage, energy density, and pulse duration become available from the physical system. Therefore, the proposed model should be interpreted not only as a regression tool, but also as the analytical core of a Digital Twin, where incoming process data are transformed into real-time estimates of soil chemical responses and can be used to support process adjustment and resource-efficient operation.

The model was built as a multi-output regression that predicts five output parameters simultaneously. Therefore, the evaluation metrics were calculated separately for each output variable. The following metrics were used to assess the quality of the model: Coefficient of Determination, Mean Square Error, Mean Absolute Error. The results are presented in Table 7 below.

Table 6: Digital twin result.

Elements	Forecast
Nitrogen	507.00
Phosphorus	2.003
Potassium	10.958
Calcium	821.32
Magnesium	1334.00

The model quality metrics in Table 7 were calculated separately for each output variable within the model evaluation pipeline. Because the target variables have substantially different numerical ranges, RMSE and MAE are presented as comparative model-error indicators rather than direct absolute deviations in the original physical units. The variable-wise assessment complements the global cross-validation results presented in Table 2 and enables comparison of predictive performance across the five output variables.

Table 7: Model quality assessment.

Parametr	R^2	RMSE (model evaluation units)	MAE (model evaluation units)
N	0.972	1.84	1.21
P	0.969	0.73	0.48
K	0.975	4.15	2.86
Ca	0.978	9.62	6.44
Mg	0.974	3.11	2.05

The results show that the model performs with high accuracy on all output parameters. To evaluate the effectiveness of the proposed model, a comparison was made with two different baseline regression models: Linear Regression and Random Forest Regression. The comparison results are presented in Table 8 below.

Table 8: Comparative analysis.

Model	R^2 (avg)	RMSE (avg)
Linear Regression	0.842	7.91
Random Forest	0.931	4.67
Proposed MLP	0.974	3.90

The comparison in Table 8 confirms that the proposed MLP model outperforms the baseline Linear Regression and Random Forest models in terms of both average coefficient of determination and average prediction error. These results indicate that the proposed architecture provides a more reliable approximation of the nonlinear relationships between voltage, energy density, pulse duration, and the resulting microelement composition.

The results show that the proposed MLP model provides much higher accuracy than traditional regression models. According to the results of the analysis, the elements Nitrogen and Calcium were identified as the most sensitive parameters for the forecast. This will allow us to optimize the model architecture in the future and focus on important input parameters.

4 CONCLUSIONS

In this study, a Digital Twin model based on artificial neural networks was developed to study the possibility of predicting the content of microelements (Nitrogen, Phosphorus, Potassium, Calcium and Magnesium) under different voltage and energy conditions. The model was found to work with high accuracy and stability, with an average coefficient of determination $R^2 = 0.974$ and a mean square error MSE = 2.896. The prediction results show that the elements Nitrogen, Calcium and Magnesium are sensitive to voltage and energy parameters, while Phosphorus and Potassium are relatively stable. This allowed analyzing the influence of various parameters on the content of elements through mathematical and visual graphs. The proposed Digital Twin-oriented model may reduce the need for repeated laboratory experiments, support resource optimization, and enable near-real-time estimation of soil chemical indicators when integrated with live process-data acquisition. The model's high-precision predictions are of scientific and practical importance in virtual simulation and process optimization. The results also show the potential for further improvement of the model in the future through deeper neural network architectures, additional data augmentation, and hyperparameter tuning. At the same time, the Digital Twin approach serves as an important scientific and practical basis for the development of innovative monitoring and optimization systems in the fields of agro-energy, agriculture, and food technologies.

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