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Hybrid neurocontrol of irrigation of field agricultural crops

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ABSTRACT

This study investigates a conceptual framework for a hybrid intelligent control system designed to optimize the irrigation practice for field crops via fertigation technologies. This research is aimed at enhancing irrigation management through the improvement of the prediction, optimization, and regulation processes. This is achieved through the incorporation of modern computational intelligence with advanced deep learning based neural networks, evolutionary optimization algorithms, and the adaptive neuro-fuzzy technique. This hybrid control framework is made up of interconnected sets of monitoring and decision-making modules. These include subsystems for evaluation of soil conditions, monitoring of plant growth and physiological development, assessment of environmental and climatic conditions, and measurements of the intensity of solar radiation. Additional systems address the preparation of the fertigation mixture and control of intelligent decision-making processes. For this system, the overall control policy is rendered through a predictive neurocontrol approach with execution on a computer platform. A recurrent deep neural model, long short-term memory (LSTM) type, provides crop growth and development parameter predictions through the ability to explore temporal dependencies in agricultural processes. Optimization in the predictive control feedback is accomplished through genetic algorithms in an adaptive manner.

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1. INTRODUCTION

Modern agricultural production more and more relies on innovative technologies developed to maintain a consistent supply of mineral nutrients during the various stages of crop growth throughout the crop cycle, namely wheat, maize, oats, cotton and sugar beet. Fertigation, or the simultaneous application of irrigation water and mineral fertilizers, is now among the most efficient of those. When combined with precise irrigation technologies—*e.g.*, drip and sprinkler systems—fertigation can significantly improve crop yield, increase fertilizer-use efficiency, and mitigate undesirable environmental impacts [1]–[4]. In any fertigation system, consideration is given to the crop type and the crop growth stage while various operational parameters are measured and updated in real time; examples of these measurements, include both the irrigation water mineral nutrient concentration, fertilizer application timing and volumes, fertigation mixture pH (acidity) and electrical conductivity (EC), soil moisture, nutrient composition, pH, and EC, environmental conditions such as air temperature, humidity, gas concentrations and wind speed, and solar radiation intensity.

Automating fertigation involves the resolution of two main issues for achieving an adequate regime for irrigation of field crops:

a. Optimization of global control–determining supply volumes, target concentrations of mineral nutrients and a target pH and EC for the fertigation solution.
b. Optimization of local control–managing the flow rates to apply individual nutrient solutions along with controlling the timing and duration for applying mineral water. Tackling these issues requires accurate predictive models and effective algorithms for optimization and for control of irrigation processes. Due to the highly nonlinear nature and difficulty in formalizing all aspects of crop growth dynamics, it has become increasingly popular to use neural networks for state recognition and predictive modelling of agricultural systems [5]–[8]. There is also a lot of literature, particularly in the area of optimization and control of complex or poorly formalized systems, including agricultural, using a variety of strategies such as evolutionary algorithms, deep learning, and neuro-fuzzy modelling [9]–[14].

However, the application of these strategies has been largely in isolation or based in subsystems rather than an integrated framework. This study presents a composite hybrid intelligent control architecture which combines these methods for smart management of irrigation systems based on fertigation technology. Predictive model neuro-control is the basis of the architecture, where a forecasting forecast has a neural network basis to produce prediction and an adaptive optimization approach is used to optimize performance.

In the proposed framework, object state recognition and forecasting are implemented using a convolutional neural network (CNN) together with a deep learning recurrent network (LSTM), while optimization and regulation of control parameters are achieved through a genetic algorithm and an adaptive neuro-fuzzy inference system (ANFIS). This hybrid structure provides a foundation for developing smart irrigation technologies in precision agriculture.

2. METHOD

Method for hybrid neurocontrol of field crop irrigation Figure 1 presents a general schematic of the hybrid neurocontrol system for the regulation of irrigation functions in field crops. The hybrid neurocontrol system contains two main components; a computer workstation and a neurofuzzy controller. The computer station collects input data from several monitor subsystems and with this data completes the first control step using the predictive-model neurocontrol methods [9], [15]. Meanwhile, the neuro-fuzzy controller operates the second control step using the ANFIS modeling algorithm [10], [16].

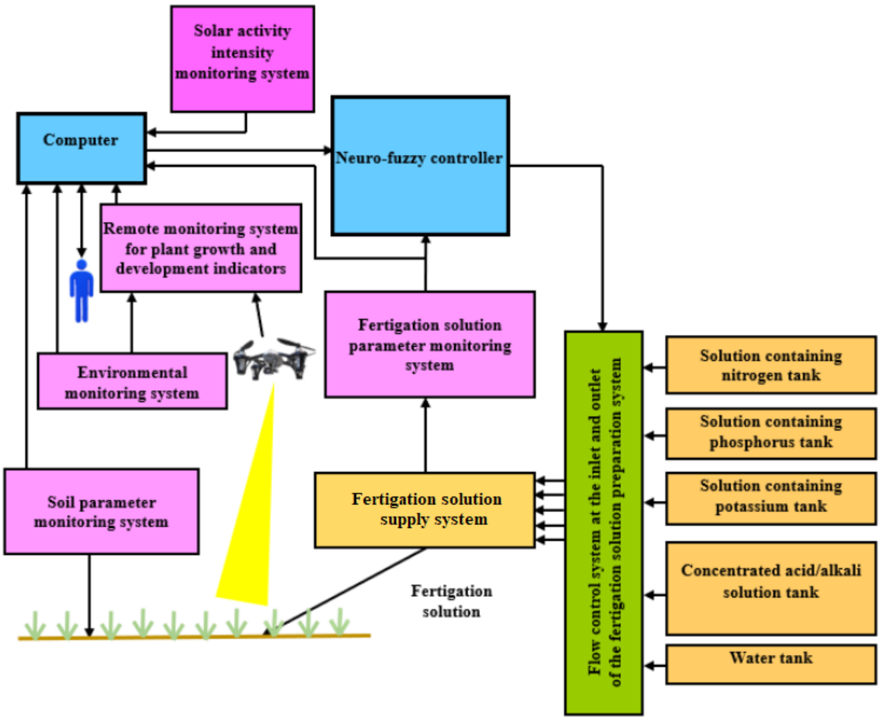


Figure 1. Generalized diagram of a hybrid neuro-control system for irrigation of field agricultural culture

Soil parameters, fertigation solution, environmental conditions, and solar field activity intensity are measured using devices placed at data collection locations. Monitoring of plant growth and development indices is performed via images collected by an unmanned aerial vehicle with subsequent processing using CNN convolutional neural networks [5], [17].

The diagram structure of the neurocontrol system for predictive modeling of field crops irrigation is shown in Figure 2. The computer part of the predictive model neurocontrol system (outlined in green in Figure 2) minimizes the functional cost of the integral error [6], [11], [12], [18], [19], predicted for $N = max(N_2, N_u), 0 \leq N_1 \leq N_2$ clock cycles ahead:

$$J(k) = \frac{1}{n}\sum_{l=1}^{n}\sum_{j=N_1}^{N_2} \rho_{y_l}(e_l(k+j))^2 + \frac{1}{m}\sum_{q}^{m}\sum_{j=0}^{Nu-1} \rho_{u_q}(u_q(k+j) - u_q(k+j-1))^2;$$
$$\sum_{l=1}^{n} \rho_{y_l} = 1;\ \sum_{l=1}^{n} \rho_{u_q} = 1, \tag{1}$$

where N_1, N_2- minimum and maximum evaluation horizons; N_u- control horizon; k - discrete time; j-iteration number; $e_l(k+j) = \hat{y}_l(k+j) - y_l(k+j)$ - error on the l-th output parameter; $\hat{y}_l(k+j)$ - model value of the l-th output parameter (parameter of plant growth and development); $y_l(k+j)$ - actual value of the l-th output parameter; ρ_{y_l} - a weighting factor reflecting the relative importance of the l-th output parameter; $u_q(k+j)$ - the q-th control variable; ρ_{u_q}- a weighting factor indicating the contribution of the change in the q-th control signal to the overall cost.

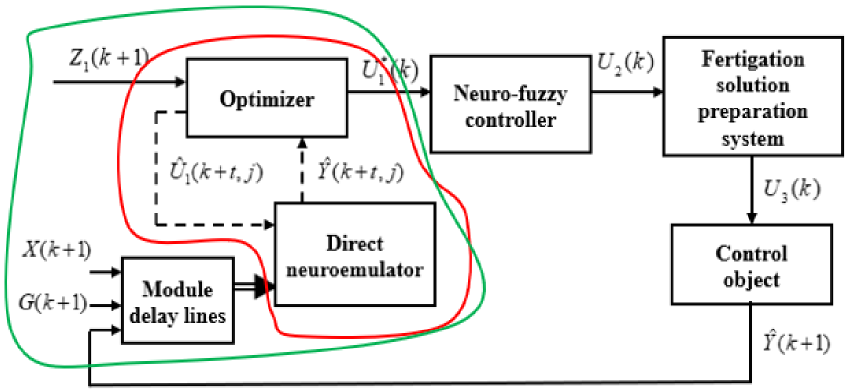


Figure 2. A block diagram of predictive model neurocontrol irrigation of field crops functional

Prediction of the future behavior of the control object $\hat{y}_l(k+j)$; $l = \overline{1,n}$ and calculation of errors $e_l(k+j)$; $l = \overline{1,n}$ is carried out by a pretrained direct neuroemulator. A direct neuroemulator can be built on the basis of n recurrent deep learning neural networks LSTM [7], [20], [21]. Each of the neural networks predicts one of the output parameters of the control object in accordance with the model of the form,

$$\hat{y}_l(k+1) = f_l(y_l(k-j), X(k-j), G(k-j), U(k-j));\ l = \overline{1,n};\ j = \overline{0, N-1}. \tag{2}$$

where $X(k-j)$ is the vector of soil condition parameters; $G(k-j)$ - the vector of environmental parameters, including the intensity of solar activity; $U(k-j)$ - the vector of global control parameters.

Different phases of vegetation $T_i \in T$ (T - a set of seasonal time intervals corresponding to different phases of plant vegetation) correspond to different parameters of plant growth and development [22], [23]. This division reduces the dimensionality of the set of output parameters for each phase of plant development, which reduces decision-making time and increases the efficiency of management.

Deep neural networks are trained by the method of error back propagation through a direct neuroemulator. The optimizer solves the problem of minimizing functionality $J(k)$ in real time. Considering the rather large step of discretization of the process of growth and development of field plants, methods that ensure finding a global optimum when the objective function is not smooth can be used for optimization. One of such methods is genetic algorithms [24]–[26].

The optimizer receives a target trajectory on clock cycle k for N clock cycles ahead. In its absence, the optimizer duplicates the value of the current setting $R(k+1)$ N times, using it as the target trajectory. The optimal control action is selected during an iterative computational process in the internal cycle of the neurofeedback system (in Figure 2, the internal cycle is outlined in red). During one control cycle, the optimizer supplies a series of different effects $\widehat{U}_1(k+t,j)$ to the input of the direct neuroemulator, where t is the depth of prediction; $0 \leq t \leq N-1$.

Receiving various variants of the system $\hat{Y}(k+t+1,j)$ behavior from a direct neuroemulator, the optimizer calculates the cost function according to formula (1) and determines the best control strategy $\{\widehat{U}_1(k,j_1),\ \widehat{U}_1(k+1,j_2),\ldots,\widehat{U}_1(k+N-1,j_N)\ \}$, which ensures the minimization of the functional $J(k)$. As a result, the input of the neuro-fuzzy controller receives a vector of settings $U_1^*(k) = \{V(k), C_i^{\mathrm{p}}(k), pH(k), EC(k)\}$; $i = \overline{1,3}$, where $V(k)$ is the mass of the fertigation solution; $C_i^{\mathrm{p}}(k)$ - the concentration values of the i-th element of mineral nutrition in the fertigation solution in the k-th cycle. On the next clock cycle, the control strategy is recalculated again.

The fertigation solution preparation system, the functional scheme of which is shown in Figure 3, includes: three tanks containing water-soluble fertilizers nitrogen, phosphorus, potassium; a water tank; a double tank containing acid and alkali (acid/alkali).

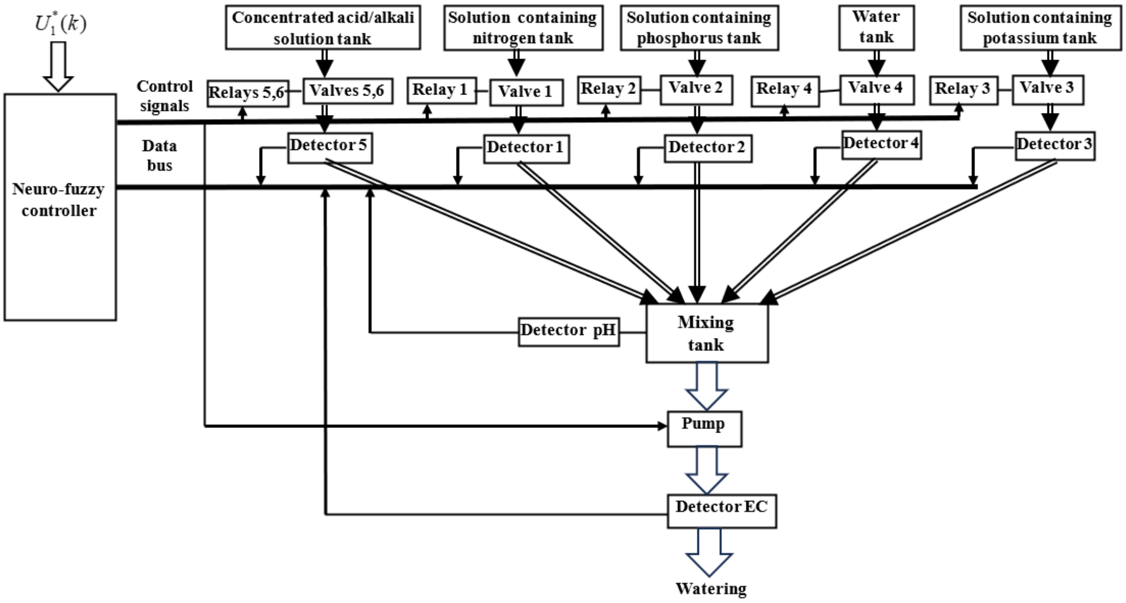


Figure 3. Functional diagram of the fertigation solution preparation system (source: own elaboration)

The operation of the fertigation solution preparation system is controlled by a neuro-fuzzy controller based on the obtained vector of settings $U_1^*(k)$ and values of concentrations of mineral nutrition elements in tanks C_i^* $[kg/l], i = \overline{1,3}$.

The neuro-fuzzy controller calculates the required volumes of solutions of mineral nutrition elements $m_i(k)$ $[l]$; $i = \overline{1,3}$ and water $m_{water}(k)$ $[l]$ supplied to the mixing tank at the k-th control cycle according to the formulas,

$$m_i(k) = C_i^{\mathrm{p}}(k)V(k)/C_i^*;\ i = \overline{1,3}; \tag{3}$$

$$m_{water}(k) = V(k) - \textstyle\sum_{i=1}^{3} m_i(k), \tag{4}$$

The filling time of the mixing tank is determined based on the mass $m_i(k)$; $i = \overline{1,3}$and $m_{water}(k)$ according to the formula,

$$T(k) = max(\ m_1(k)/v_{\ 2\ 3\ water\, water\ max\ \ 3max\, 2max\, 1max} \tag{5}$$

where $v_{watermax_{3max_{2max_{1max}}}}$ is the maximum allowable consumption of substances at the inlet of the mixing tank.

The consumption of substances $v_i, i = \overline{1,3};\ v_{water}$ at the inlet and the time of supply of substances $t_i, i = \overline{1,3};\ t_{water}$ to the mixing tank are determined by the formulas,

$$v_i(k) = m_i(k)/T(k), i = \overline{1,3}; v_{water}(k) = m_{water}(k)/T(k), \quad (6)$$

$$t_i(k) = m_i(k)/v_i(k), i = \overline{1,3}; t_{water}(k) = m_{water}(k)/v_{water}(k). \quad (7)$$

The neurofuzzy controller outputs control signals to controlled electromagnetic relays 1-4, which open or close solenoid valves 1-4. The solenoid valves are opened for a time $t_i(k), i = \overline{1,3}; t_{water}(k)$ calculated according to the formulas (8). The supply of solutions of mineral nutrition components and water to the mixing tank is carried out with the flow rates $v_i(k), i = \overline{1,3}; v_{water}(k)$ calculated according to the formulas (7). Control of the flow rate of mineral nutrition components and water is carried out by flow sensors 1-4. After the filling time of the mixing tank $T(k)$ has expired, the solenoid valves are closed.

After closing the solenoid valves, the irrigation solution preparation system goes into standby mode for a time interval corresponding to the interval between the two mixing processes, which is calculated in days. In this case, the *pH* value in the mixing tank is corrected. Then the pump supplies the prepared fertigation solution to the irrigation water pipeline. The process of preparation and supply of fertigation solution for irrigation is resumed in the next cycle of the system operation with new setpoints ($V(k+1)$, $C_i^{\mathrm{p}}(k+1), i = \overline{1,3}$, $pH(k+1)$, $EC(k+1)$).

The *pH* of the fertigation solution in the mixing tank is monitored by a *pH* sensor. A neuro-fuzzy controller controls the amount of acid or alkali flow at the outlet of valves 5, 6. according to the following rules,

$$\begin{cases} if\ pH > pH(k) & \text{then } v_{ac} = V_{ac}/t_{giv.} \& v_{al} = 0; \\ if\ pH < pH(k) & \text{then } v_{al} = V_{al}/t_{giv.} \& v_{ac} = 0; \\ if\ pH = pH(k) & \text{then } v_{ac} = v_{al} = 0, \end{cases} \quad (8)$$

where v_{ac}, v_{al}- the consumption of acid and alkali at the outlet of the solenoid valves 5, 6; V_{ac}, V_{al}- the required volume of acid and alkali; $t_{giv.}$- the set time for the supply of acid or alkali.

Decision-making on controlling the supply of acid or alkali in a neuro-fuzzy controller is based on the ANFIS model [6], [13]. In conclusion of this section, “methods,” it should be clarified that a deep LSTM neural network is used as a predictive mathematical model. The construction of this neural network and its practical application in the prediction of dynamic systems described by multidimensional time series is well known. It is cited in many scientific works, including scientific articles by the authors. To avoid self-citation, these articles are not included in the list of references.

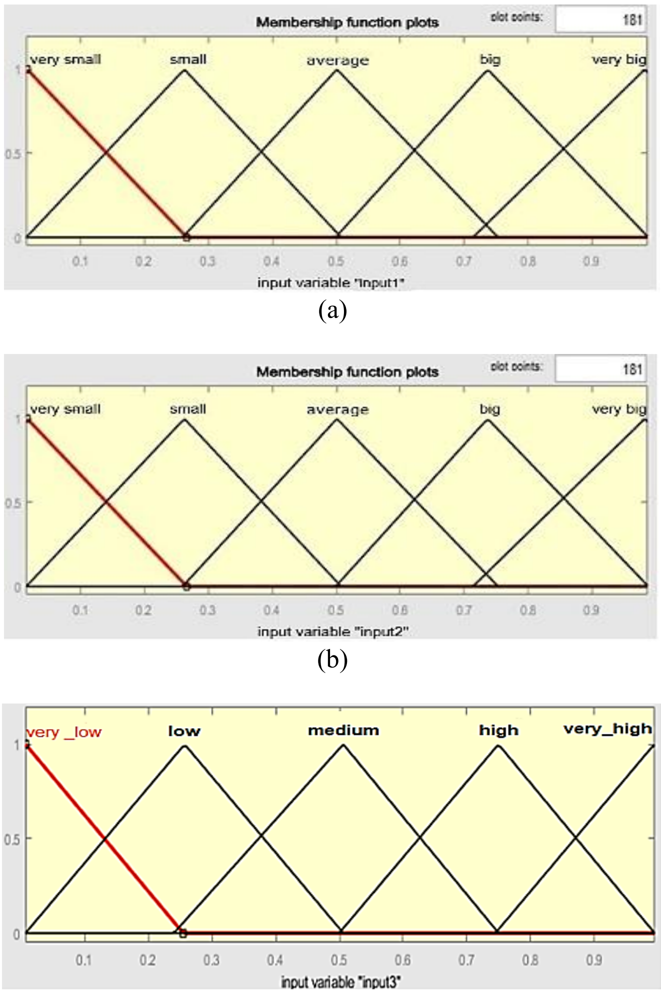
3. RESULTS AND DISCUSSION

The input variables for the neuro-fuzzy decision-making model for acid and alkali are: the value (input 1) of the current difference *pH-pH*(*k*), volume (input 2) and the current *pH* value (input 3) of the fertigation solution in the mixing tank. The volume and *pH* level of the fertigation solution in the mixing tank are set in relative units ($V(k)/V_{max}$) and (pH/pH_{max}). The output variables (output 1 and output 2) are variables V_{ac} and V_{al}, for each of which its own neuro-fuzzy decision model is built (ANFIS 1 and ANFIS 2).

The construction of a neuro-fuzzy model in relation to the process of drip irrigation of cotton was carried out in MATLAB 2021b using the ANFIS edit editor. The results of constructing a neuro-fuzzy model are shown in Figures 4(a)-4(c), Figures 5(a)-4(b), and Figures 6(a)-6(c). The ANFIS 2 model can be constructed in a similar way. Determination of the total concentration $C_\Sigma(k)$ of mineral nutrition components in the fertigation solution is carried out by measuring its electrical conductivity with an *EC*(*k*) sensor. Moreover, a high EC value of the solution indicates a high concentration of mineral nutrition components in the fertigation solution.

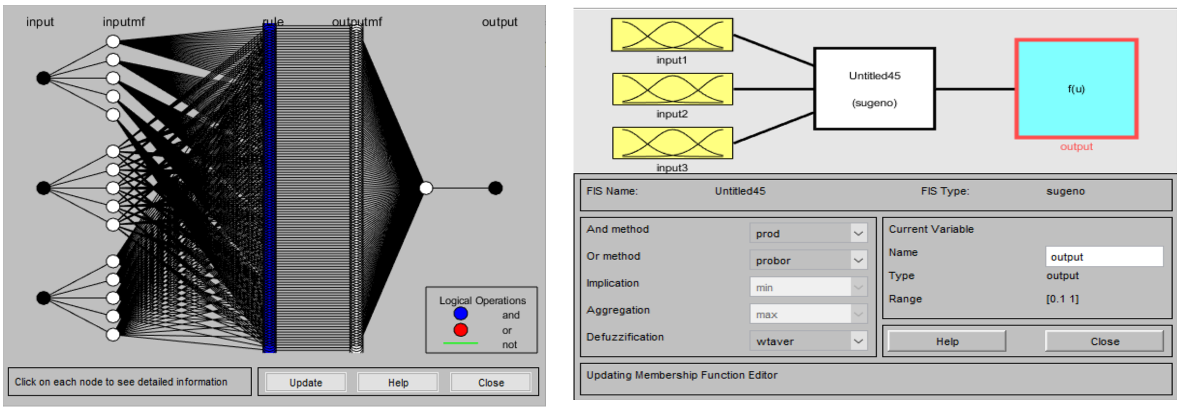
At high concentrations of mineral nutrition components in the soil solution, the absorption of water and nutrients by plants slows down sharply [27], [28]. Based on this, it is logical to set the volume flow rate $v_\Sigma(k)$ of the fertigation solution inversely proportional to its *EC*(*k*). The relationship between $v_\Sigma(i)$ and the *EC*(*i*) can be determined experimentally, or based on a survey of experts, and entered into a database table in the form of a series of variations $\mathrm{EC}(1) < \mathrm{EC}(2) <\ldots< \mathrm{EC}(N)$ and their corresponding values $v_\Sigma(1) >$

$v_\Sigma(2) <\ldots< v_\Sigma(N)$. The neuro-fuzzy controller determines the current value based on the rule: $v_\Sigma(k) = v_\Sigma(i)$, where $v_\Sigma(i)$ is the tabular value of the volumetric flow rate of the fertigation solution.



(c)

Figure 4. Membership functions of the input variables (a) for a variable input 1, (b) for a variable input 2, and (c) for a variable input 3



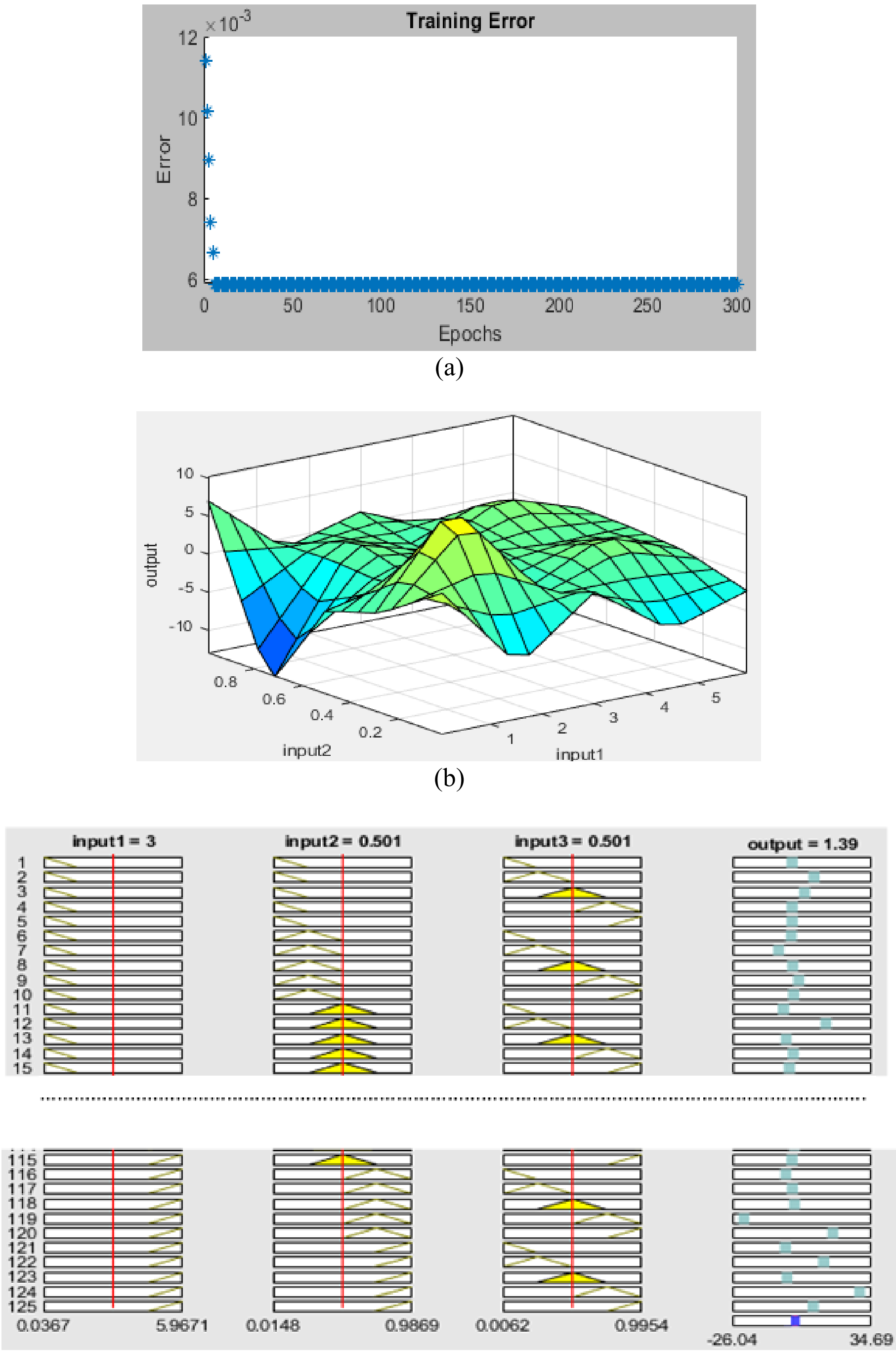
(a) (b)

Figure 5. The results of the construction of the ANFIS 1 neuro-fuzzy model (a) architecture of synthesized ANFIS 1 and (b) a window of a fuzzy Sugeno type system

The table value $v_\Sigma(i)$ is selected based on the condition:

$$\Delta_i = \min_{i=1,N} \sqrt{(EC(k) - EC(i))^2} \tag{9}$$

where $EC(i)$ - the i-th tabular value of the EC, which corresponds to $v_\Sigma(i)$; N - the amount of data in the table. The block diagram of the algorithm for hybrid neurocontrol of irrigation of field crops is shown in Figure 7.



(a)

(b)

(c)

Figure 6. The results of the construction of the ANFIS 1 neuro-fuzzy model (a) training of a synthesized neuro-fuzzy network, (b) graphical view of the dependence of the system output on the inputs, and (c) visualization of fuzzy inference for pH control

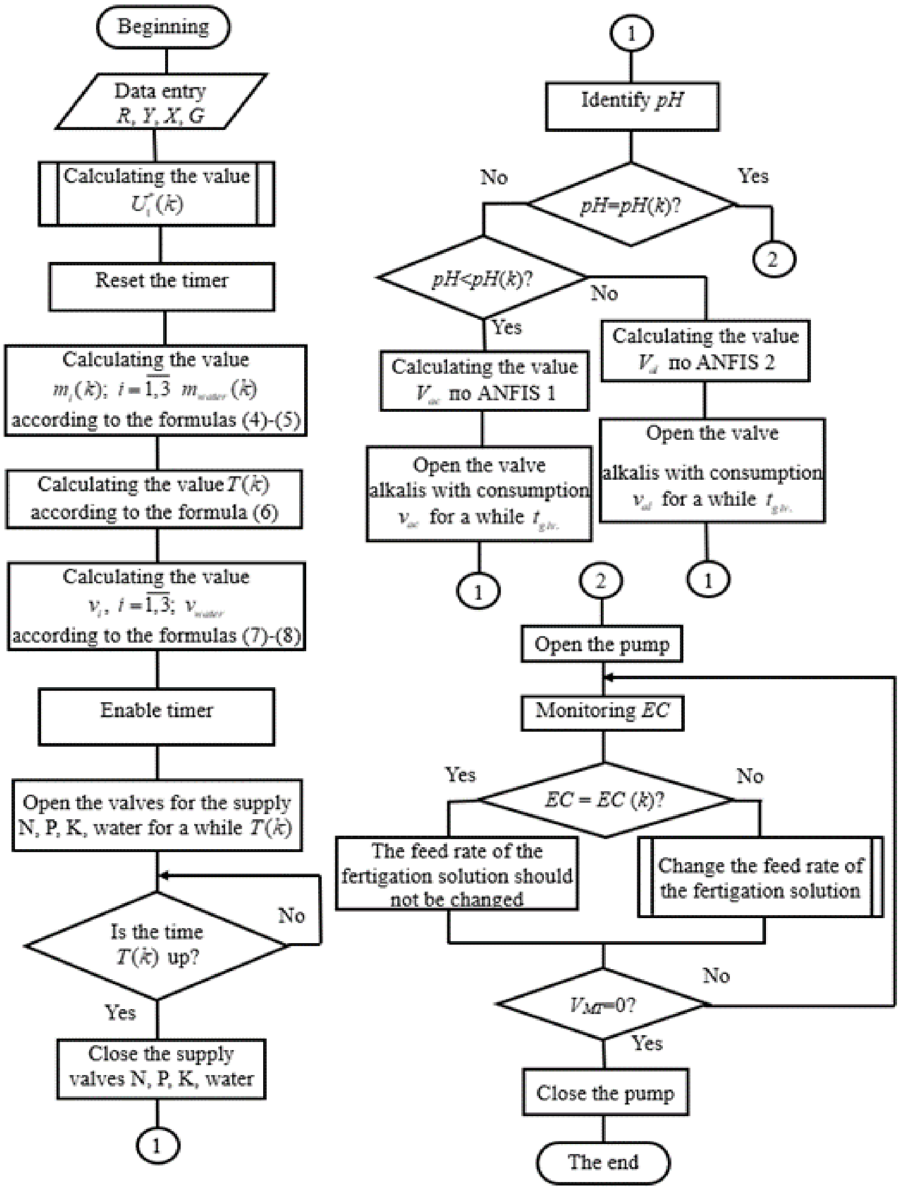


Figure 7. Flowchart of the algorithm of hybrid neurocontrol of irrigation of field crops VMT- the volume of fertigation solution in the mixing tank

4. CONCLUSION

The hybrid neurocontrol irrigation system for field crops has several advantages: a modular principle simplifies the development of the system, since each module can operate independently, allowing for the addition of modules and adjustment of operation as required; The use of LSTM neural networks once again allows for the development of a predictive model neurocontrol algorithm that provides high accuracy in predicting developmental trends of field crops, which is demonstrated through practical examples. Neuro-fuzzy control is simple to implement in existing software environments and easily conforms to outside conditions; The structure of a neuro-fuzzy controller is an effective option for control over the delivery of mineralized water to the root system of field crops because it uses scientifically founded methodologies for controlling plant development.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Dilnoza B. Yadgarova		✓	✓	✓			✓		✓	✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest

DATA AVAILABILITY

Research data are not shared

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