Irrigation management information system model with integrated elements of artificial intelligence

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Abstract. The research is devoted to the development of new, self-adapting irrigation management systems allowing the control decisions reliability increasing based on the consideration of the terrain natural features in the service area. A model of irrigation management with integrated elements of artificial intelligence is proposed, which can significantly increase the forecast accuracy for the total water consumption of agricultural crops and the expected dates of irrigation. A distinctive feature of the proposed model is the use of an artificial intelligence segment to adapt the parameters of the total water bioclimatic model consumption to the conditions of a real area. The model assumes that adaptation occurs automatically through self-learning of a neural network integrated into the system. To train a neural network it is proposed to use hybrid information systems based on the combined use of sensor and computational methods of irrigation control. Such “double” systems can be implemented on test fields and adapted to the area decisions can already be extended to neighboring or similar areas.

1. Introduction

Modern neural networks have already become a powerful tool capable to solve many practically significant problems that previously could not be solved without the personal participation of a human [1, 2]. As a component of artificial intelligence, neural networks are successfully used in pattern recognition, in classification and forecasting problems, in the approximation of complex nonlinear functions, and in other spheres. This kind of technology has many advantages but perhaps the most important of them is the self-learning ability. The possibility of continuous learning, adaptation to changing conditions allows you to scale technologies confidently, get individually oriented accurate solutions. Another important feature and advantage of neural networks as an artificial intelligence technology is the variety of input data used, the ability to evaluate arbitrarily complex, multifactorial, nonlinear dependencies, to obtain solutions taking into account practically all factors affecting the process (object). The neural network also knows how to work and even processes quite well the so-called “big data”, when among a large number of indicators it is necessary to find (filter) only the “necessary” ones. This allows you to work with the global information space, highlighting and using the information that improves the solutions accuracy. As a whole, these, as well as a number of other advantages, which we will not focus on here, make it attractive to use neural networks in irrigation management problems solving [3, 4, 5].
2. Materials and methods

However, neural networks, constituting the most promising direction of artificial intelligence technology, nevertheless, are not without disadvantages. In fact, there are many disadvantages in these technologies, this is the problem of networks retraining, when instead of looking for patterns in the input data, the network, in fact, "remembers" the answers, the problem of "anomalous" data in the training set, the problem of "black box" [6, 7]. The neural network does not allow evaluating the patterns, and, often, there is no way to understand how this or that solution was obtained. And if for the nodes where the training "pairs" of data were used, the solutions are the most accurate, then between them the answers may not have any physical significance. And this is an objective fact that the neural network is in no way connected with the "physical significance".

Taking into account these disadvantages, one can hardly bank on success by shifting all the responsibility for making decisions about the irrigation relevance or forecast on the neural network. Irrigation control is a complex multi-approach process, with the implementation of logical sequences, while the neural network has only an “input” and a solution, and in principle is not capable of sequential computations. But there are certain areas where the use of neural networks could significantly increase the accuracy of irrigation control systems even within the framework of well-known algorithmic solutions [8, 9]. And in this regard, it is necessary not to set for artificial intelligence a global task of irrigation management but to use its advantages at the level of individual modules integrated into the general management system.

3. Results and discussion

There are several areas where the implementation of artificial intelligence technologies in irrigation management problems solving is justified. In this research we will try to reveal the prospects for the neural networks implementation in only one of them. The idea is as follows. Irrigation management today is based on two strategies, the first is based on the analytical method and the second on the sensor technologies usage. Sensor technologies are undoubtedly among the new, promising solutions in the field of irrigation management, however, this approach also has its disadvantages.

First, to form an objective judgment on the irrigation necessity, a set of spatially separated sensor data is required, which needs an extensive sensor network. Sensor technologies are still quite expensive and the creation of an extensive sensor network is implemented when growing only the most valuable agricultural crops, as a rule. Secondly, the sensors allow the irrigation requirement assessing on the plot only at a given time, while forecasting and making an optimized irrigation schedule can be based only on analytical methods. Thus, computational methods in irrigation control problems solving remain in demand in the sensor technologies development. On the other hand, computational methods also have their disadvantages associated primarily with insufficient forecast accuracy, according to the modern standards. Insufficient forecast accuracy is associated with the simplification of the models used in comparison with real processes in irrigated areas.

In particular, we faced such a problem while the total water consumption model selecting as the main item of soil water balance in seeds of various agricultural crops. The official methodology of the Food and Agriculture Organization of the United Nations for the total water consumption calculating is, in fact, the water-heat balance Penman-Montein model:

\[
ET_{\text{st}} = \frac{0.408\Delta(G - R_n) + 900 \theta \Delta t}{\Delta + 34(G - R_n) + \theta},
\]

where \(ET_{\text{st}}\) is the total water consumption of the reference crop, mm/d; \(R_n\) is the radiation balance at the vegetation cover border, mJ / m² per day; \(G\) is the density of the soil heat flow mJ / m² per day; \(t\) is the air temperature at a 2 m height from the soil surface, estimated as an average daily indicator; \(\theta\) is the indicator of the air masses (wind) movement speed at a 2 m height from the soil surface; \(e_s\) is the vapor pressure in the atmosphere at full saturation, kPa; \(e_a\) is the actual value of the same indicator, kPa; \(\Delta\) is the vapor pressure curve slope, kPa/°C; \(\gamma\) is the psychrometric constant, kPa/°C.

Perhaps, this is the most detailed total water consumption model, from the physics’ point of view, that gives quite accurate solutions for the reference crop in retrospective calculations. However, while irrigation planning with the predictive calculation it is necessary for accurate solutions that all the
parameters included in the Penman-Montein model are sufficiently reliably predicted, which is currently not a solved problem. In Russia, the modified model of total water consumption by N.N. Ivanova has gained some popularity:

\[ ET_0 = k_1 d_\phi f(v), \]

where \( ET_0 \) is the potential evapotranspiration, mm; \( d_\phi \) is the air humidity deficit, mb; \( k_1 \) is the evaporation energy factor, mm/mb; \( f(v) \) is the wind function.

The model provides accurate solutions during actual meteorological data usage, however, by solving forecast problems the same problems arise as while the Penman-Montein total water consumption model implementation. Parameters forecast errors included in this model, especially for such a dynamic factor as wind, reduce the predicted accuracy of calculations to a level that is not acceptable in modern irrigation management systems. To link the potential evapotranspiration, the solution of which is provided by the model under consideration, with the total water consumption of a particular agricultural crop, bioclimatic coefficients are used.

From the point of view of the parameters forecast reliability included in the calculation model, the most acceptable option is to use simple, one-parameter models based on one, usually easily predictable, meteorological parameter. Such models are known and became quite widespread, at one time:

\[ E = k_b \sum d_\phi; \ E = k_b \sum t , \]

where \( E \) is the crops total water consumption, mm, \( d_\phi \) is the average daily air humidity deficit, mb; \( t \) is the average daily air temperature, \( ^\circ C \); \( k_b \) is the bioclimatic coefficient that establishes the relationship between the meteorological parameter adopted as a basis and the total water consumption of agricultural crop.

The disadvantage of this approach in the agricultural crops total water consumption modeling is the high variability of bioclimatic coefficients, the values of which change under the influence of a whole complex of factors not taken into account in the model. To neutralize this variability, the bioclimatic coefficients for these models were determined not only for each crop separately, but also for each region characterized by its own climatic features. This increased the predictive accuracy of the models, but this level remains insufficient for use in modern information systems for irrigation management. It is necessary to adapt the bioclimatic coefficients of the model at the landscape level. However, even such segmentation does not exclude significant errors, since the meteorological and soil factors combination influence, the water supply, biometric deviations in the crop development, as well as many other factors on which crop evapotranspiration depends remain unaccounted. As a whole, these factors create a certain image that characterizes the state of this complex system and for each such image the answer is a certain value of the bioclimatic coefficient. Definitely, such a problem cannot be solved by conventional methods, and inappropriately either. This work is just proposed to be transferred to artificial intelligence.

Figure 1 shows an irrigation management model with similarly integrated artificial intelligence elements. The model assumes a hybrid organization of sensor technologies and analytical algorithms, which together make it possible to assess the requirement for the next irrigation, estimate the date of the next irrigation, and make a forecast for the irrigation regime for the short and medium term.

The data sources in the model are sensors, a specially organized database, as well as a global information space, which makes it possible to assess in full the factors influencing system which determines the total water consumption dynamics. These data sources are organized in a certain way into a system, their central link is the database. In general, the sensor system can have different degrees of configuration, but at least it should provide data collection on soil moisture in the active layer. The sensors usage that makes it possible to assess the soil temperature, temperature and relative humidity in the seeds environment and at a 2 m height, the dynamics, intensity and volume of atmospheric precipitation, indicators characterizing the radiation regime of seeds, the wind speed and direction, make it possible to create the most accurate image of the conditions on plot, determining the total water consumption of agricultural crops.
The actual soil moisture data is used to make a decision on the watering requirement. The decision is made on the basis of a quantitative comparison of the actual soil moisture in the zone of moisture consumption by the agricultural plants roots with a threshold level \( W_{thr} \). It is assumed that the threshold level of pre-irrigation soil moisture is a priori known value, which is included in the database. Depending on the inertness of the irrigation control system, it is allowed to increase the threshold level of pre-irrigation soil moisture by \( \Delta W \):

\[
\Delta W = e \cdot T_{in} \cdot m_{1W},
\]

where \( e \) is the dynamics of water consumption in the estimated curve interval, \( m^3/ha \) per hour; \( T_{in} \) is the system inertia time, hour; \( m_{1W} \) are the moisture reserves in the active soil layer corresponding to the 1% moisture level, \( m^3/ha \).

If watering is not required, the execution of subsequent algorithms of the irrigation control system is interrupted, and information about the actual soil moisture at the measurements time is entered into the database. If the irrigation requirement decision is made, the procedure for calculating the irrigation rate, the development of the technological process and the task for irrigation is launched. The known soil characteristics of the irrigated area (\( \sum F_{soil} \)) are used to calculate the irrigation rate.

**Figure 1.** Irrigation management model with integrated elements of artificial intelligence.
The analytical segment of the proposed model assumes the determination of the actual soil moisture by calculation. A quantitative assessment of the actual soil moisture is carried out on the basis of solving the water balance equation. The calculation, as a rule, is carried out for the future, using forecast agrometeorological information, and then soil moisture is determined for some forecast date.

The retrospective agrometeorological information, \( \sum F_{\text{meteo}} \), can also be used, and then the actual soil moisture is determined by the calculation The data on the current humidity is transmitted to the decision-making module about the irrigation requirement, and the described above procedures are repeated in exactly the same way as when using sensor information. During forecast calculations carrying out, the forecast irrigation date is determined, an irrigation schedule for the irrigated massif can be drawn up and optimized.

The analytical segment calculation of the proposed model is based on the bioclimatic model of the agricultural crops total water consumption (\( dE \)), based on one, the most easily predicted agrometeorological parameter. The most reliable forecasts today can be obtained from air temperature (\( dt \)), but other meteorological parameters can also be used, for which regional values of bioclimatic coefficients (\( \delta_{\text{reg}} \)) are determined. The proposed model allows the system to self-learn and refine the regional values of bioclimatic coefficients, taking into account the cumulative influence of local factors.

To train the system, the model assumes the use of sensory information on the actual soil moisture. Additionally, meteorological (\( \sum F_{\text{meteo}} \)), hydrological (\( \sum F_{\text{hydro}} \)) information, data on soil properties (\( \sum F_{\text{soil}} \)), which source can be a database, a global information space, are used, but received locally sensor data are preferable. This information is used to compile the water balance equation, the solution of which allows you to obtain the actual values of the total water consumption and to clarify the bioclimatic coefficients. The values of bioclimatic coefficients obtained in this way are actually real (\( \delta_{\text{exp}} \)) against the background of the combined influence of a factors complex that determine the instantaneous (fixed) image of the conditions prevailing in the irrigated area. The data on this complex of factors (\( \sum F_{\text{cond}} \)), constituting a fixed image of the conditions prevailing in the irrigated area, along with the actual estimates of bioclimatic coefficients, are used to train the neural network. The latter, upon accumulating a sufficient amount of data, learns itself to predict the updated values of bioclimatic coefficients, taking into account the cumulative effect of influencing factors, already for any calculation period, and also with the possibility of spreading to irrigated agricultural landscapes with similar conditions.

The parameters of the trained neural network are copied into the working module of the system artificial intelligence, which is responsible for generating the updated values of bioclimatic coefficients (\( \delta_{\text{gen}} \)). Locally adapted bioclimatic coefficients replace the use of regional bioclimatic coefficients, due to which the accuracy of bioclimatic model solutions and forecasts, consequently, can be significantly increased. The model assumes that the combined implementation of sensor and analytical technologies to solve irrigation management problems is not necessary for each of the reclaimed areas served. These can be irrigated fields used as test plots, the data from which is used to train the neural network. Then the obtained solutions can be extended to neighboring or similar territories, where irrigation management is carried out exclusively by the calculation method.

### 4. Conclusion

An irrigation management model with integrated elements of artificial intelligence has been developed, which allows to increase significantly the forecast accuracy for the total water consumption of agricultural crops and the expected dates of irrigation. A distinctive feature of the proposed model is the artificial intelligence segment implementation to adapt the parameters of the bioclimatic model of total water consumption to the conditions of a real area. The model assumes that adaptation occurs automatically through self-learning of a neural network integrated into the system. The bioclimatic model parameters usage adapted in this way can be extended to neighboring or similar territories, where irrigation management is carried out exclusively by the calculation method.

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