Intelligent Speed Control of Water Sprinklers Based on Artificial Neural Networks

Dmitry A. SOLOVYOV

Saratov State Vavilov Agrarian University

1, Teatralnaya square, Saratov, 410012, Russian Federation

7(8452)233292

Galina N. KAMYSHOVA

Saratov State Vavilov Agrarian University

1, Teatralnaya square, Saratov, 410012, Russian Federation

7(8452)233292

gkamichova@mail.ru

Dmitry A. KOLGANOV

Saratov State Vavilov Agrarian University

1, Teatralnaya square, Saratov, 410012, Russian Federation

7(8452)233292

Sergey M. BAKIROV

Saratov State Vavilov Agrarian University

1, Teatralnaya square, Saratov, 410012, Russian Federation

7(8452)233292

Nadezhda N. TEREKHOVA

Saratov State Vavilov Agrarian University

1 Teatralnaya square, Saratov, 410012, Russian Federation

7(8452)233292

Abstract

Results of researches of possibility and efficiency of introduction of intelligent control systems, namely neural network speed control, in control systems of water sprinklers of circular action are presented in this article. The size of an irrigation norm essentially depends on speed, and this dependence is not linear and is caused by many stochastic factors. The results of comparing the theoretical and actual values of "irrigation norm-rate" dependencies show their significant differences, which affects the quality of irrigation. Traditional approaches based only on physical

modelling of technical processes and connections often make it difficult to find effective solutions. Technological advances that increase data collection and analysis capabilities can significantly improve the efficiency of engineering solutions. An approach based on the model of intelligent data analysis, namely the model of neuro velocity control, is proposed. Neuro-control, leads to a possible implementation of better and more efficient management of sprinkling equipment.

Keywords: irrigation; control; speed; neural network.

Introduction

Over the past 50 years, global agricultural production has increased 2.5-3 times, and the growth of cultivated areas was about 12%. According to forecasts, the increase in production will occur due to its intensification on existing cultivated lands. At the same time, the role of irrigation is increasing, as more than 40% of the growth of world food production and 60% of grain production falls on irrigated land.

The development of digital technology also influences trends in sprinkling technology. One of the key areas is intellectualization, automation and robotization. Among foreign vehicles, we can give examples of Zimmatic, Valley, Reinke, which are already actively following this path. In Russia, scientific research in the field of improving sprinkler technology was aimed primarily at improving the design parameters of sprinklers, reducing energy consumption while maintaining the technological parameters of irrigation, reducing working pressure, reducing the intensity and improving the structure of rain, ensuring higher irrigation uniformity and machine productivity (Olgarenko, 2018; Solovyov, Zhuravleva, 2018). And only in the last few years efforts have been made to introduce elements of automation and robotization (Solovyov, Zhuravleva, Bakirov, 2019) in irrigation technology.

Technological advances that increase data collection and analysis capabilities can significantly improve the efficiency of engineering solutions. In Kamilaris and Prenafeta-Boldú's (2018), a review of research papers that use deep learning techniques applied to various agricultural and nutritional problems is presented. The specific problems of agriculture, the models and structures used, sources, nature and preliminary processing of the data used are analyzed. Systems based on artificial intelligence methods (artificial neural networks, fuzzy logic, machine learning algorithms and much more) are increasingly being used to control technical objects. A review of such methods is presented in Kamilaris, Kartakoullis, and Prenafeta-Boldú's work (2018). In the works of Lozoya et al. (2016) and Parra-Boronat et al. (2018), the applications of the above methods for increasing the efficiency of irrigation are considered. Modern tools for intelligent data analysis, in-depth training, etc. provide improved accuracy by solving complex relationships in large volumes

of technical parameters and have great potential. So, on their basis, decision support systems are developed in irrigated agriculture (Navarro-Hellin et al., 2016; Song et al., 2016). In this regard, it seems expedient to conduct theoretical and experimental research towards the intellectualization of sprinkler technology. The presented research is focused on the development of a neuroregulator of speed to improve the efficiency of sprinkling equipment.

Methods

It is well known that water sprinkler is a complex hydro, electro, mechanical dynamic system with, as a rule, non-linear dependencies. The size of the irrigation norm must comply with agricultural requirements and is one of the key characteristics of water sprinklers.

As it is known, the irrigation norm issued during the motion of the machine is equal to

$$m = \frac{600Q}{2\pi RV_{cp}}$$

where-average truck speed, m/min (Solovyov, Zhuravleva, 2018; Abdrazakov et al., 2016).

According to the hydraulic model of the sprinkler, the irrigation rate depends on the speed. The most widely used water sprinklers in the practice of irrigated agriculture in Russia. At their operation, as researches have shown, the size of the irrigation norm essentially depends on speed, and this dependence is not linear and is caused by many stochastic operational factors such as soil preparation, slope of a field, type of soil, humidity of a soil.

The results of comparison of theoretical and actual values of "irrigation norm-speed" dependencies show that the actual speed of wide-capacity water sprinklers is 9.5-13.6% less than the specified one and with the increase of irrigation norm this difference increases, and the type of machines is not a significant factor (Solovyov, Zhuravleva, 2018). At the same time, the reduction in speed leads to a 7-10.5% increase in irrigation rates. All this requires constant adjustments to the operating mode of the machine. The review of researches shows that the existing methods before that time represented experimental researches with construction of mathematical models of control objects (in this case irrigation norm) and development of recommendations on adjustment of modes of operation of water sprinklers to achieve optimal parameters. We use methods of intellectual data analysis, namely artificial neural network apparatus to optimize irrigation rate management depending on the speed. Field experiments on data collection were conducted in Engels district of Saratov region on Gagarin irrigation system. According to agroclimatic conditions the study area belongs to the zone of insufficient and unstable humidification, the climate is moderately continental with a predominance of clear and low clouds days per year, hot and dry summers, cold

and snowy winters, short spring and short autumn, and a high probability of spring and autumn frosts.

Results

In most cases, modern sprinklers use an electric drive with an AC three-phase asynchronous motor or a hydraulic drive. On the control panel by changing the duration of the electric motor is set the speed of the last trolley, with the movement of the other trolleys in the same mode of "start / stop" with the autonomous control of the synchronization device motion. The travel time of the last support trolley is set using a percentage timer, which determines the total speed of the entire installation. The current management system appears to be clearly not optimal and needs to be improved. Development of models of intellectual management, namely management on the basis of artificial neural networks, seems to be relevant.

Neuromanagement of dynamic objects is a new promising area at the intersection of such disciplines as automatic control, artificial intelligence, neurophysiology (Beale et al., 2015). In the literature examples of practical application of neural networks for the decision of problems of management of various objects are described. So, in the works by Al-Bareda and Pupkov (2016) and Belov et al. (2018), the results of the application of methods of neurocontrol of electric motors and robotic objects are presented. The use of artificial intelligence to optimize green roof irrigation is discussed (Tsang et al., 2016). Modeling of a neural network for predicting leaf temperature in wine grapes for calculating the index of water stress of the crop is given (King, Shellie, 2016). There are reviews of methods of management with the help of neural networks, as well as algorithms of selection of management quality criteria (Schmidhuber, 2015).

Currently, the development of control systems for agricultural machinery is underway, providing remote control of work, collection, processing and analysis of data on the progress of technological processes based on the use of computer technologies, hardware and software complex for precision agriculture (Soloviev, Zhuravleva, Bakirov, 2019). In addition, the development of modern technological base - measuring devices (sensors), microcontrollers, microcomputers, tablets and smartphones, allows to implement neuro-control on almost any water sprinkler. The following schematic diagram of the device is proposed in Figure 1.

Figure 1. Device circuit diagram

Introduction of neuro-control methods into sprinkler control systems allows improving the quality of functioning of complex systems with non-linear objects and connections. Directly in the computing module of the system is synthesized neural controller, which for a given moment of time at known values of input disturbances using a neural network finds the value of the control action with its subsequent implementation to the control module. A functional speed control circuit to minimize the difference between the calculated and actual values of irrigation rates is shown in Figure 2.

Figure 2. Functional control circuit with integrated neuroregulator

The current speed signal from the measuring unit is fed to the input of the measurement module. Corresponding input and output data arrays are used to synthesize the neural network to find the control value, minimizing the deviation of calculated and actual values of irrigation norms. From the computing module the signal goes to the control module, which is either a direct control system of the sprinkler for robotic irrigation systems or to a demonstration device (computer, smartphone or tablet) that allows the operator to make a decision on the control action.

For synthesis of the neurocontroller (Cheon et al., 2015), it is possible to use different software products such as Matlab and Python. We use the algorithm implemented in Matlab environment (Neral Network Toolbox package). At the first stage the initial data of the operating wide-capacity

sprinklers, necessary for the synthesis of the neurocontroller, were collected. Table 1 shows a sample from the data set of actual driving speeds and irrigation norms.

Table 1. Field study data sampling

№	Depth of irrigation, m ³ /ra	Running speed, m/min
1	323	0,2
2	331	0,23
3	431	0,15
4	443	0,18
5	548	0,12
6	559	0,11

The task of synthesis of a neurocontroller is not trivial and requires meticulous work on selection of neural network topology, training parameters (Duffy, 2016). Ultimately, the neural network, which is the model of the controller and correctly outputs the output signal on the teaching set, should be obtained. To check the adequacy, the models simulate the output signal of the system on a test set. Based on the results of the simulation on the test set, it can be concluded that the neural model generates an output signal corresponding to the expected signal, while the error (difference between the required and actual value of irrigation norm) is minimal. The neural network must be able to transmit process dynamics.

The basic circuit of simulation in the Matlab/Simulink software environment (Dyakonov, 2016) is shown in Figure 3.

Figure 3. Basic circuit of simulation in Matlab/Simulink systems

The task of neural network management (Figure 4) is to bring the actual value of irrigation norm as close as possible to the reference (required) and to optimize resources such as water and energy.

Figure 4. Neural network speed control algorithm

We use two neural networks: the network identifier and the network regulator (Beale et al., 2015). Network-identifier is used for identification and emulation of mathematical model of the object and further training of network-regulator. Both networks are built on a multilayer perceptron scheme (Schmidhuber, 2015). The number of neurons in the hidden layers varies. The Levenberg-Marquardt algorithm is considered as the learning algorithm of the neural network (Belov et al., 2018). On the basis of the collected data of wide-capacity sprinklers (Table 1), the optimal parameters of the neural network were established. The learning process is shown in Figure 5.

Figure 5. Matlab neural network training

The values of weight matrices w_1 w_2 and displacement vectors b_1 and b_2 are presented in Table 2.

Table 2. Values of weighting matrices and displacement vectors

Input layer						
w_1	6.1084	1.4482	-2.4494	-1.4166	3.0076	1.5825
b_1	-6.7541	-1.4888	1.9937	0.6833	0.6662	0.2074
Output layer						
w_2	0.0901	0.1404	-0.5105	-0.8927	0.0042	0.5454
b_2	-0.6501	-	-	-	-	-

This network is then connected to the controller. The network weights are considered constant and only the weights of the regulator's network are adjusted, minimizing the discrepancy between the response of the reference model and the defined neural networks to the same input signal. After training, the controller is used in the control loop.

In the course of algorithm modeling we get visualization of control results with neural controller (3), as well as the reference model (1) and control without correction (2). On the basis of the modeling data we build graphs of transients in time (t) (Figure 6). As can be seen from the above charts, control with a neural controller in the structure almost repeats the dynamics of the reference model, while control without correction has the worst dynamics.

Figure 6. Transition processes

Conclusion

The main objective of the irrigation management system model development was achieved by means of the neural controller simulation.

An approach based on the model of intelligent data analysis, namely the model of neuro velocity control, is proposed. Most irrigation systems use the control of the start/stop controller type. These controllers cannot provide optimal results for different time delays and different system parameters. Proposed approach based on artificial neural network. The main modeling parameter is speed. The

model based on management with a neural controller leads to the implementation of management close to the benchmark, which allows reducing the gap between the specified and actual irrigation rate to 2.3-3.6%, unlike the existing 7-10%. Another advantage is that neural controllers do not require prior knowledge of the system and are able to adapt to changing conditions, unlike traditional methods. And finally, the development of a modern digital base - measuring devices, microcontrollers, microcomputers, tablets and smartphones - allows to implement neuro-control on almost any sprinkler according to the proposed principle scheme. This optimizes irrigation parameters and reduces the power and water consumption of the sprinkler with neural controller in the control system.

References

- Abdrazakov, F.K., Zatinatsky, S.V., Povarov, A.V., Pomorova, A.V., Trushin, Y.E. (2016). Hydrodynamic model of watering of the fregat sprinkling system equipped with deflector nozzles. *International Journal of Pharmacy & Technology*, 8(4), 27063–27071.
- Al-Bareda, Y.S., Pupkov, K.A. (2016). The algorithm for decision of control system synthesis problem by the artificial neural networks' method. *RUDN Journal of Engineering Researches*, 2, 7-16.
- Beale, M., Hagan, M., Demuth, H. (2015). *Neural Network Toolbox™ User's Guide*. The Math Works, Inc.
- Belov, M.P.; Nosirov, I.S.; Phuong, T.H. (2018). Electric servo drive of turning lathe control system using neural generalized predictive control. *ETU LETI*, 4, 45-53. Retrieved from: https://izv.etu.ru/assets/files/izvestiya_leti_4_2018_p073-080.pdf
- Cheon, K., Kim, J., Hamadache, M., Lee, D. (2015). On Replacing PID Controller with Deep Learning Controller for DC Motor System. *Journal of Automation and Control Engineering*, 3(6), 452–456. DOI: 10.12720/joace.3.6.452-456
- Duffy, D.G. (2016). *Advanced Engineering Mathematics with MATLAB, Fourth Edition*. Chapman & Hall/CRC.
- Dyakonov, V.P. (2016). *MATLAB and SIMULINK for radio engineers*. DMK Press.
- Kamilaris, A., Kartakoullis, A., Prenafeta-Boldú, F.X. (2017). A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture*, 143, 23–37. DOI: 10.1016/j.compag.2017.09.037

- Kamilaris, A., Prenafeta-Boldú, F.X. (2018). Deep learning in agriculture: a survey. *Computers and Electronics in Agriculture*, 147, 70–90. DOI: 10.1016/j.compag.2018.02.016
- King, B.A., Shellie, K.C. (2016). Evaluation of neural network modeling to predict non-water-stressed leaf temperature in wine grape for calculation of crop water stress index. *Agricultural Water Management*, 167, 38–52. DOI: 10.1016/j.agwat.2015.12.009
- Lozoya, C., Mendoza, C., Aguilar, A., Roman, A., Castello, R. (2016). Sensor-Based model driven control strategy for precision irrigation. *Journal of Sensors*, 31, 1–12. DOI: 10.1155/2016/9784071
- Navarro-Hellin, H., Martinez-del-Ricon, J., Domingo-Miguel, R., Soto-Valles, F., Torres-Sances, R. (2016). A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture*, 124, 121–131. DOI: 10.1016/j.compag.2016.04.003
- Olgarenko, G.V. (2018). Realization of imports phase-out program of irrigation equipment production in Russian Federation. *Melioration and water management*, 1, 44-47.
- Parra-Boronat, L., Rocher, L., Lioret, J., et al. (2018). Design of a WSN for smart irrigation in citrus plots with fault-tolerance and energy-saving algorithms. *Network Protocols Algorithms*, 10, 95-115. DOI: 10.5296/npa.v10i2.13205
- Schmidhuber, J. (2015). Deep Learning in neural networks: An overview. *Neural Networks*, 61, 85-117. DOI: 10.1016/j.neunet.2014.09.003
- Shadskikh, V.A., Ryzhko, N.F., Kizhaeva, V.E., Ryzhko, N.V., Ryzhko, S.N., Smirnov, E.S. (2020). *Recommendations for the efficient use of irrigated lands, taking into account the introduction of long-term unused irrigated areas into circulation*. Engels.
- Soloviev, D., Zhuravleva, L., Bakirov, S. (2019). Robotic Irrigative Complex with Intellectual Control System CASCADE. *XVIII International Scientific and Practical Conference "Modern Trends in Agricultural Production in the World Economy"*, 145-156.
- Solovyov, D.A., Zhuravleva, L.A. (2018). Influence of the water sprinkler movement mode on the irrigation rate. *Upper Volga Bulletin of AIC*, 1(41), 38-43.
- Song, X., Zhang, G., Liu, F., Li, D., Zhao, Y., Yang, J. (2016). Modeling spatio-temporal distribution of soil moisture by deep learning-based cellular automata model. *Journal of Arid Land*, 8, 734-748. DOI: 10.1007/s40333-016-0049-0
- Tsang, S.W., Jim, C.Y. (2016). Applying artificial intelligence modeling to optimize green roof irrigation. *Energy and Buildings*, 127, 360-369. DOI: 10.1016/j.enbuild.2016.06.005