Application of intelligent control systems for liquid level process-control

Anwendung intelligenter Steuerungssysteme zur Prozesskontrolle von Flüssigkeitsständen

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Abstract — Plants with process variable "level" have nonlinear characteristics, which make them difficult to control. Conventional control systems such as PID controllers can't guarantee constant quality of process variable regulation. Intelligent systems such as fuzzy logic can cope with this task but with the cost usage of expert knowledge. On the other hand, neural networks are still poorly applied to process control. The purpose of this article is to explore the possibilities of applying neural networks and machine learning in the control of level regulation.

Zusammenfassung — Anlagen mit der Prozessgröße „Füllstand" haben nichtlineare Kennlinien, die ihre Steuerung erschweren. Herkömmliche Regelsysteme wie PID-Regler können keine konstante Qualität der Prozessgrößenregelung garantieren. Intelligente Systeme wie die Fuzzy-Logik können diese Aufgabe bewältigen, allerdings mit dem Einsatz von Expertenwissen. Andererseits werden neuronale Netze immer noch kaum zur Prozesssteuerung eingesetzt. Der Zweck dieses Artikels besteht darin, die Möglichkeiten der Anwendung neuronaler Netze und maschinellen Lernens bei der Steuerung der Pegelregulierung zu untersuchen.

I. INTRODUCTION

Level regulation is widely used in many areas of industry. In various installations, it is necessary to maintain a certain material balance, both of liquids and bulk materials. The prevalence of this process, as well as the multitude of options for automatic level maintenance, makes this topic interesting to explore.

Level regulation is required in those cases when a certain supply of substances necessary for the proper running of a technological process must be guaranteed, and also through which disturbances on other parameters are reduced. Level control systems make up about 10% of the total number of control systems for typical technological processes. The level of liquids in various buffer tanks is regulated, by means of which a certain material balance is maintained in a given apparatus or group of apparatus. The water level in drum steam boilers is regulated, the liquid level in various evaporation plants, chemical reactors is regulated. In the first case, there is level regulation during hydrodynamic processes, and in the other cases - during heat and mass exchange processes [1].

In addition to liquids, in practice it is necessary to adjust the level of bulk materials - grain, sand, felt, cement, etc. In this case, the level adjustment is carried out during mechanical processes.

II. LEVEL CONTROL SYSTEM

A typical level control setup consists of a tank system, a signal converter, and a computer with software designed to operate the system. The tank system consists of two connected tanks. Level maintenance takes place in the first. It is a cylinder with a certain cross-section and height. The water in it is supplied by a membrane pump and has the possibility to flow into the second one by means of two channels. The condition of the channels is determined by the position of two ball valves. The second tank is the sump of the system. The water from the first flows into it and returns through the pump. The current level in the cylindrical tank is read by a pressure sensor (differential manometer) [2]. The technical parameters of the example laboratory system are:

- Maximum level of the vessel – Hmax = 60cm ± 1cm;
- Section of the cylindrical tank – A = 78.53 cm2;
- Section of both outflow channels – Sn = 0.2827 cm2;
- Maximum input flow rate from the pump – Qmax≈110ml/sec.

A mathematical description of the laboratory system was obtained in the following way - in the general case, the equation that describes the change in the level h of a liquid in a given vessel, with an imbalance of the input and output mass flows, is:

$$\frac{dh}{dt} = Q_{in} - Q_{out} \tag{1}$$

where: Q_{in}, Q_{out} are volume flow, respectively, of input and output flow. When the vessel has a free flow of the liquid, the Bernoulli equation for a free-flowing liquid is valid:

$$Q_{out} = a_z s \sqrt{2gh} \tag{2}$$

where:
a_z – dimensionless leakage coefficient;
s – cross-section of the outflow opening;
g – ground acceleration.
Substituting into the above equation and converting gives:

$$A\frac{dh}{dt} = k_s U_s - a_z S_n \sqrt{2gh} \tag{3}$$

where:
k_s – transmission coefficient of the pump;
U_s – pump voltage;
h – current level of the liquid in the vessel.

It can be seen from the equation that the control object is non-linear. In this case, in order to achieve a high quality of regulation in the entire operating range, it is necessary to use specific control algorithms, which in most cases include some nonlinearity. The implementation of such algorithms requires special technical means and sufficient computing capacity of the control device [3].

III. FUZZY LOGIC

The mathematical model of level control systems in a free-drain vessel are non-linear, which usually requires complex control algorithms. In this case, the methods of artificial intelligence are extremely convenient. One example is the use of fuzzy logic in the form of a fuzzy controller.

The fuzzy controller has the structure shown in Fig. 1.

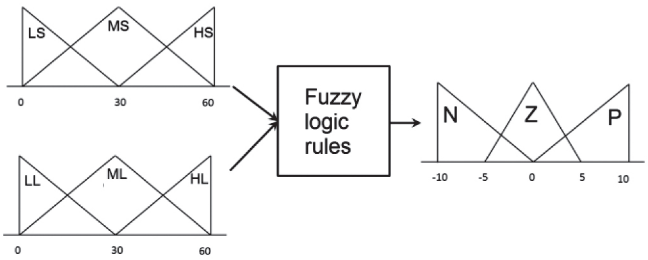


Fig. 1. Structure of the fuzzy controller

The input linguistic variables take the following terms:

- Variable “SetPoint” – “Low SetPoint”, “Medium SetPoint” and “High SetPoint”;

- Variable “Level” - “Low Level”, “Medium Level” and “High Level”.

Each term is assigned the corresponding fuzzy set defined by a membership function as follows:

- Variable “SetPoint” – Term “Low SetPoint” – membership function is triangular with start point 0, vertex 0 and endpoint 30. Term “Medium SetPoint” – membership function is triangular with start point 0, vertex 30 and endpoint 60. Term “High SetPoint “ - the membership function is triangular with a start point of 30, a vertex of 60 and an end point of 60.

- Variable “Level” - Term “Low Level” - membership function is triangular with start point 0, vertex 0 and end point 30. Term “Medium Level” - membership function is triangular with start point 0, vertex 30 and end point 60. Term “High Level” - the membership function is triangular with a start point of 30, a vertex of 60 and an end point of 60.

The output linguistic variable accepts the following terms - “Negative”, “Zero” and “Positive” to which are mapped fuzzy sets set with the following membership functions “Negative” - a triangular function with a start point of -10, a vertex of -10 and an end point of 0, “Zero” - triangular function with start point -5, vertex 0 and end point 5 and “Positive” - triangular function with start point 0, vertex 10 and end point 10.

The fuzzy controller can provide constant control quality at all operating points by compensating for non-linearity. The disadvantage of fuzzy controllers is that they require considerable expertise to set up.

IV. NEURAL NETWORKS

Another part of artificial intelligence methods is artificial neural networks. Their setup is based on training with pre-generated input-output data, which does not require significant expert knowledge. Artificial neural networks are not yet widely applied in modern control systems. One of their possible applications is for the adjustment of non-linear objects, such as the level adjustment object. There are different types of neural network structures that are applicable for different purposes. For example, convolutional neural networks are particularly suited to image processing and recognition. However, most structures describe a static relationship between input and output data. For control systems purposes, it is necessary to use dynamic descriptions. Dynamic descriptions require that the output values depend not only on the current value of the input, but also on the states of the input at some previous time points. In order to obtain a dynamic neural network, it is necessary in the structure to introduce the possibility of storing values and their subsequent use in the calculation of the output.

The structure of artificial neural networks that has memory and allows the modeling of dynamic systems is known as recurrent neural networks (RNN). A typical structure of a recurrent neural network is shown in Fig. 2.

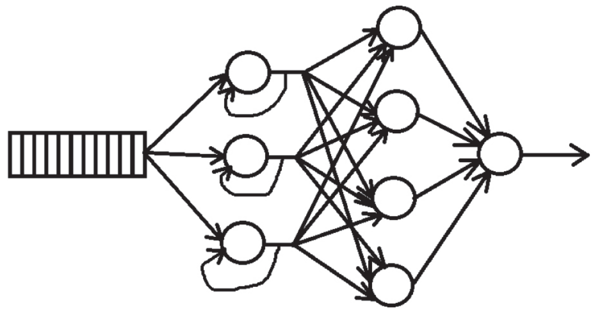


Fig. 2. Recurrent neural network

A Python program code was created that simulates the response of the control object. The program code looks like this:

```
import math
import matplotlib.pyplot as plt

def levelreg(Q, T0):
    A = 0.007853
    s = 0.00002827
    z = 0.95
    g = 9.81
    b = z*z*s*s*2*g - 2*((A*A)/(T0*T0))*levelreg.h1
    a = ((A*A)/(T0*T0))
    c = ((A*A)/(T0*T0))*levelreg.h1*levelreg.h1 - Q*Q
    D = b*b - 4*a*c
    h = (-b+math.sqrt(D))/(2*a)
    levelreg.h1 = h
    return h

levelreg.h1 = 0

Q = [0,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]
H = []
step = 0.00005
T0 = 5

for q in Q:
    H.append(levelreg(step*q,T0))

plt.plot(range(0,T0*len(H),T0),H)
plt.show()
```

Simulations were made with different values of the input flow rate, with which the operability of the simulation model was checked. The results of the simulations are shown in Figures 3,4 and 5.

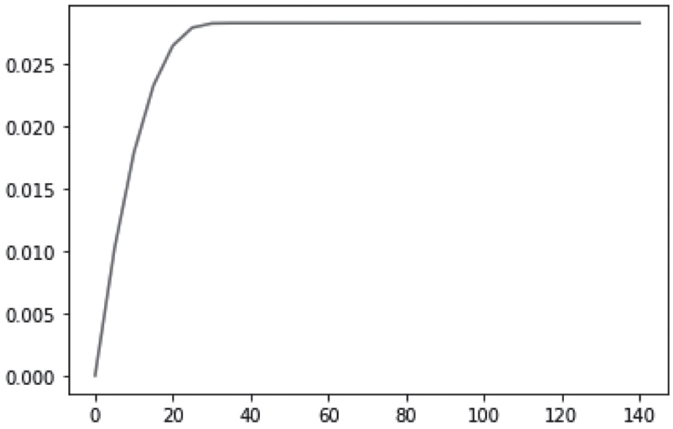


Fig. 3. Input flow 20 ml/s

If the input flow is 20 ml/s level in tank will be around 3 cm.

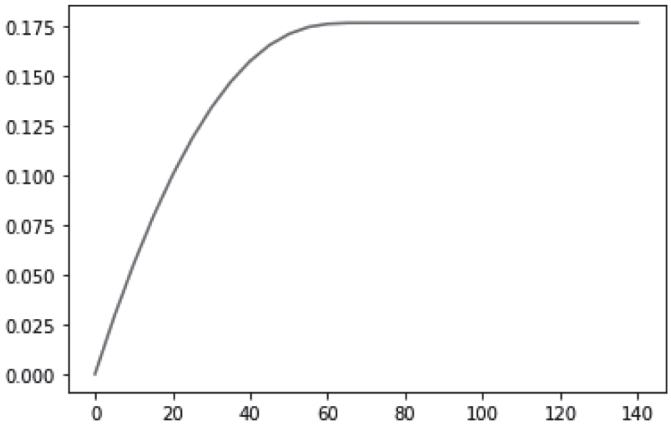


Fig. 4. Input flow 50 ml/s

If the input flow is 50 ml/s level in tank will be around 18 cm, and time to reach steady state is larger than with 20 ml/s flowrate.

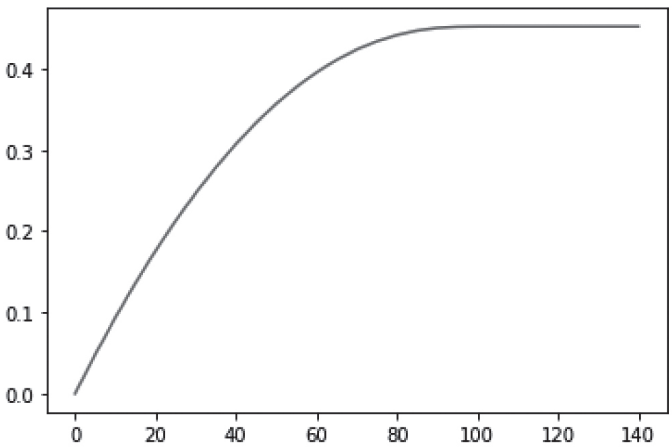


Fig. 5. Input flow 80 ml/s

If the input flow is 80 ml/s level in tank and time to reach steady state is largest. This is because of nonlinearity.

Input and output data were generated for the training of an artificial neural network that describes an optimal regulator for the object under study. The input data for the regulator represents the difference between the set (desired) value for the level and the actual one at the moment - E. The output data is the control signal that must be sent by the regulator to the control object - U. The time between two values for the input and output data is fixed every 5 seconds. The data is formatted into arrays of the appropriate dimension using the "Numpy" library. A neural network was built which contains an input layer, a hidden recurrent layer with 4 neurons and an output layer with one neuron. The activation function of all neurons is linear. The complete structure of the neural network is shown in Table 1.

TABLE 1 NEURAL NETWORK STRUCTURE

Layer (type)	Output Shape	Parameters #
Input Layer	(29, 1)	0
Simple RNN Layer	(29, 4)	24
Dense Layer	(29, 1)	5
Total params: 29 Trainable params: 29 Non-trainable params: 0		

The neural network is trained for 500 epochs at which the accuracy is satisfactory.

The Python program code that builds and trains the neural network is as follows:

```
from tensorflow import keras
import numpy as np

in3 = keras.Input(shape=(len(E),1))
out3 = keras.layers.SimpleRNN(4, activation='linear',
                    return_sequences=True,
                    return_state=False)(in3)
out4 = keras.layers.Dense(1,activation='linear')(out3)
rnn3 = keras.Model(inputs=in3, outputs=out4)
rnn3.summary()

rnn3.compile(optimizer='rmsprop',   loss='mean_squared_
error')
hist3 = rnn3.fit(np.reshape(np.array(E),(1,len(E),1)),
              np.reshape(np.array(U),(1,len(U),1)),
              epochs=500)
plt.plot(hist3.history['loss'])
plt.show()

indata2 = np.ones(len(E))*0.5
indata2[0] = 0

outdata2 = rnn3.predict(np.reshape(indata2,(1,len(E),1)))

t2 = np.arange(0,len(E))
plt.plot(t2,indata2,t2,outdata2[0,:,0])
plt.show()
```

The neural network is incorporated into a control system with the simulated control object. In the simulations, the results shown in Figures 6, 7 and 8 were obtained.

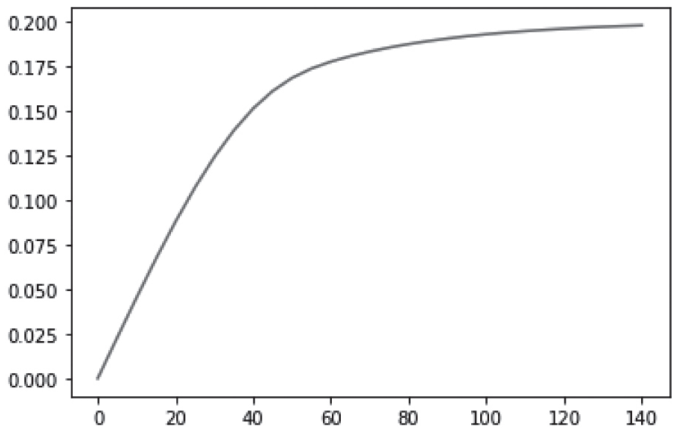


Fig. 6. Level Set Point 20 cm

Set point for level 20 cm is obtained for around of 100 seconds.

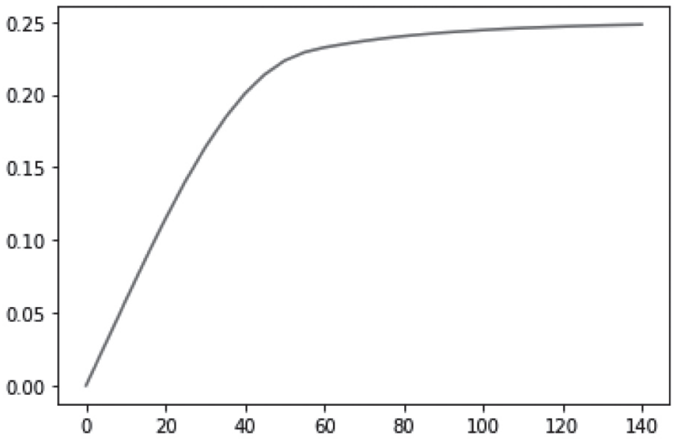
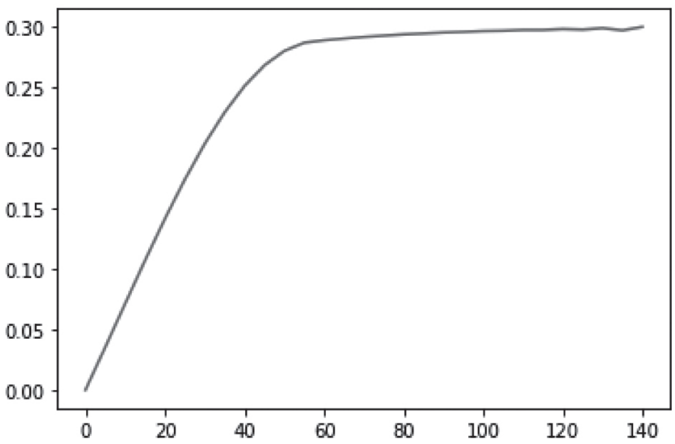


Fig. 7. Level Set Point 25 cm

Fig. 8. Level Set Point 30 cm



Set point for level 25 cm is obtained for around of 80 seconds. And set point for level 30 cm is obtained for around of 60 seconds.

V. CONCLUSION

It can be seen that the adjustment is not of constant quality at all operating points, but this is due to the data used to train the neural network. But despite the small amount of training data, the neural network achieves satisfactory quality. The quality of regulation is better compared to a linear control system and also the neural network shows significant development potential. With more precise training, it is possible to achieve a constant quality of adjustment in the entire working range.

VI. REFERENCES

[1] A. Marinchev, V. Karlova-Sergieva, Experimental study of laboratory bench “level control”. Proceedings of the Technical University - Sofia, v. 64, book 1, 2014., pp. 195-200

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[3] A. Marinchev, Application of modern algorithms for level control with LabView. Proceedings of the Technical University - Sofia, v. 66, book 2, 2016., pp. 205-200