NN-ANARX Model based Control of Liquid Level using Visual Feedback

Department of Computer Control, Tallinn University of Technology
{kristina.vassiljeva, aleksei.tepljakov, eduard.petlenkov}@ttu.ee

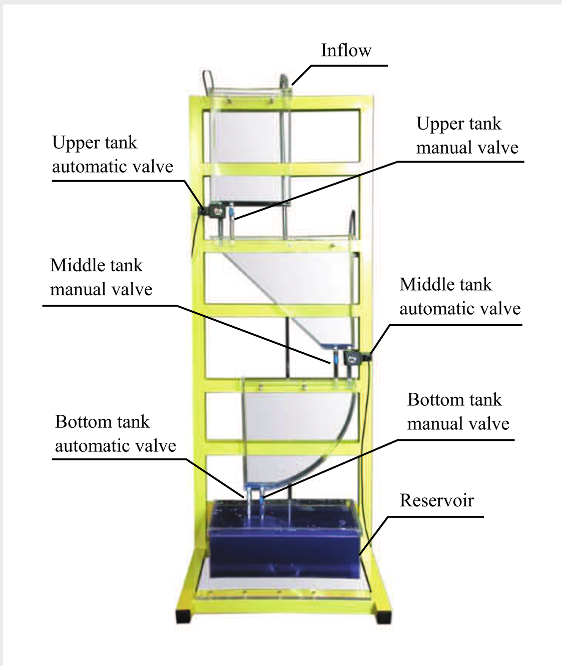
TUT

Control Lab
www.a-lab.ee

Contribution

First, we explore the abilities of Neural Network based Additive Autoregressive eXogenous (NN-ANARX) models in computational intelligence based controller applications, whereby the goal is to control the liquid level in a Multi Tank system. The liquid level is measured using visual detection courtesy of an embedded system application, based on the Raspberry Pi computer. Thereby visual feedback based control is achieved. The communication between Raspberry Pi and the control system running in MATLAB/Simulink environment is provided over a WLAN network, which also creates an additional opportunity to study network delay based effects on the control system under investigation. In fact, a prediction module is implemented to compensate for the delay caused by the on-board video processing and communication.

Multi Tank system



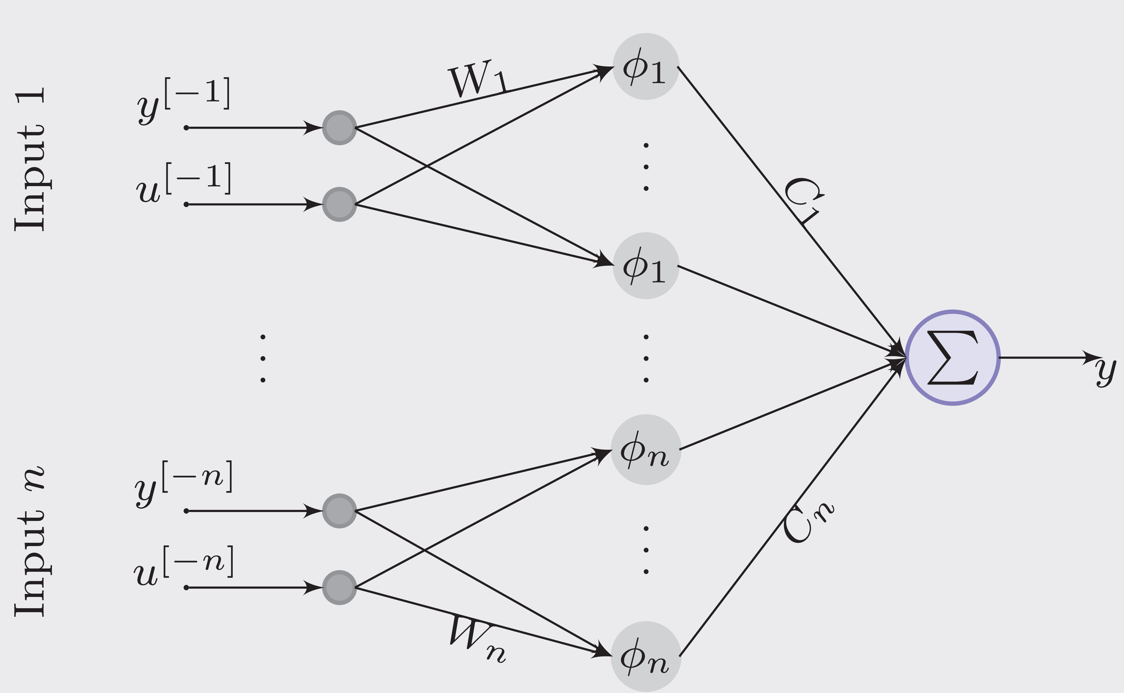
Dynamical behavior of the plant can be described in a continuous time domain by the following differential equations

$$\begin{aligned}\dot{x}_1 &= \frac{1}{aw}\left(u - D_1 x_1^{\alpha_1}\right),\\ \dot{x}_2 &= \frac{x_2}{cwx_2 + bwH_2}\left(D_1 x_1^{\alpha_1} - D_2 x_2^{\alpha_2}\right),\end{aligned} \qquad (1)$$

where $u = q$ is inflow, a, b, c are lengths of the upper and top and bottom of the middle tanks, w is a width of the tanks, H_i is maximum fluid level in the ith tank, x_1, x_2 are levels in the upper and middle tanks, respectively.

NN-ANARX

A schematic diagram of the neural network, representing ANARX structure, is depicted below.

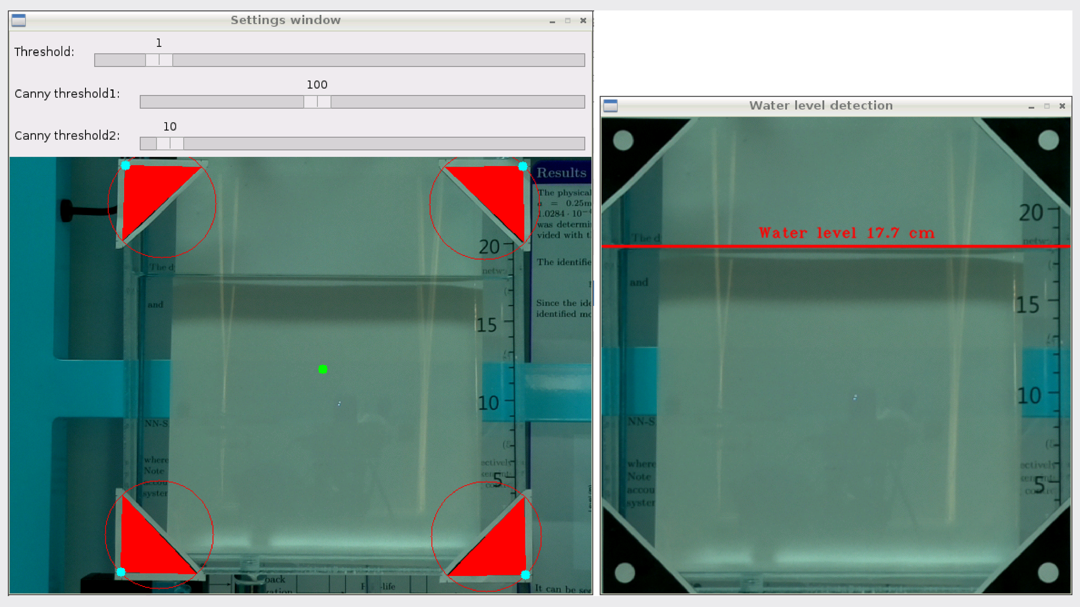


$$y^{[n]} = \sum_{i=1}^{n} C_i \phi_i \left(W_i \left[y^{[n-i]} \quad u^{[n-i]} \right]^{\mathrm{T}} \right), \qquad (2)$$

The remarkable property of the described ANARX structure is that it can always be linearized by the output dynamic feedback.

Visual Feedback

Visual system is assembled using credit-card sized computer Raspberry Pi and Raspberry Pi CSI camera.



Water level detection consists of 3 stages:

- Choice of the ROI (Region of Interest);
- Application of the Canny operator for edge detection;
- Hough transformation is applied: longest horizontal line shows the water level.

Communication with MATLAB is done using UDP protocol via laboratory wireless network.

Control Method

The dynamic output feedback can be written by using parameters of the neural network as

$$\eta_1 = C_1\phi_1\left(W_1 \left[y \quad u\right]^{\mathrm{T}}\right) \qquad (3)$$

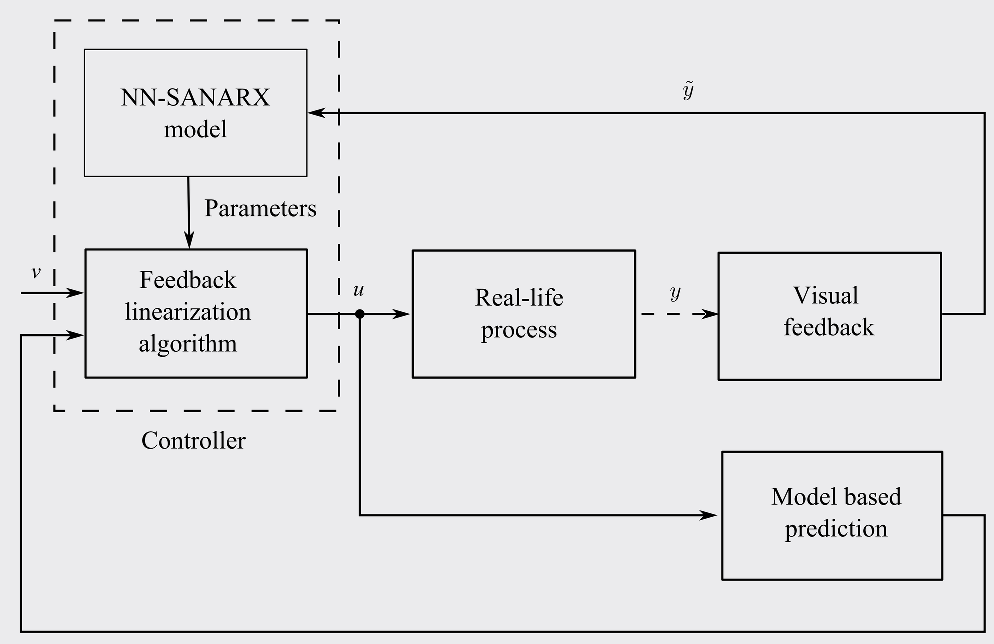
and

$$\begin{aligned}\eta_1^{[1]} &= \eta_2 - C_2\phi_2\left(W_2\left[y \quad u\right]^{\mathrm{T}}\right)\\ &\vdots\\ \eta_{n-2}^{[1]} &= \eta_{n-1} - C_{n-1}\phi_{n-1}\left(W_{n-1}\left[y \quad u\right]^{\mathrm{T}}\right)\\ \eta_{n-1}^{[1]} &= v - C_n\phi_n\left(W_n\left[\tilde{y} \quad u\right]^{\mathrm{T}}\right).\end{aligned} \qquad (4)$$

In order to simplify the calculation of the control signal in (3), we assume that $\phi_1(\cdot)$ is a linear function, resulting in a simplified structure of the neural network known as a NN-SANARX model. It means that (3) can be rewritten as follows

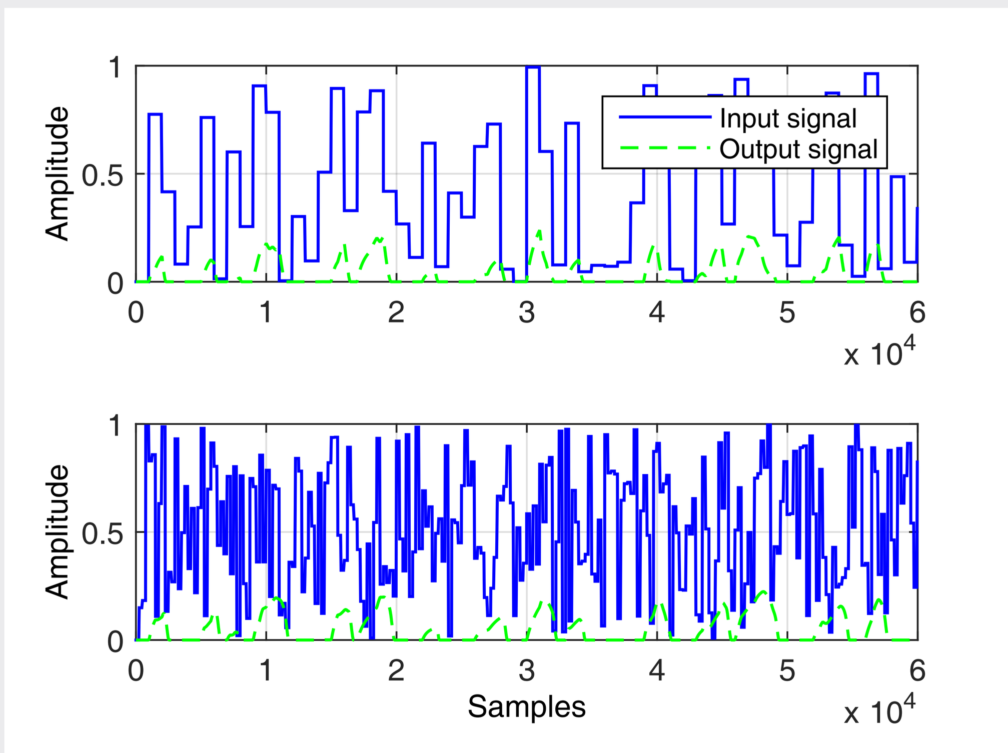
$$u = T_2^{-1}(\eta_1 - T_1\tilde{y}), \qquad (5)$$

where T_1 and T_2 are the first and second elements of the vector C_1W_1, respectively. Note that T_2 has to be a nonsingular square matrix. This fact has to be taken into account on the identification stage. The overall structure of the corresponding control system is represented below.



MIMO Control Case

For the upper tank data is gathered using visual feedback, for the other tank the built in level sensor is used. This can be a good example of the system where data is collected asynchronously.
NN training data set is presented in following figure.



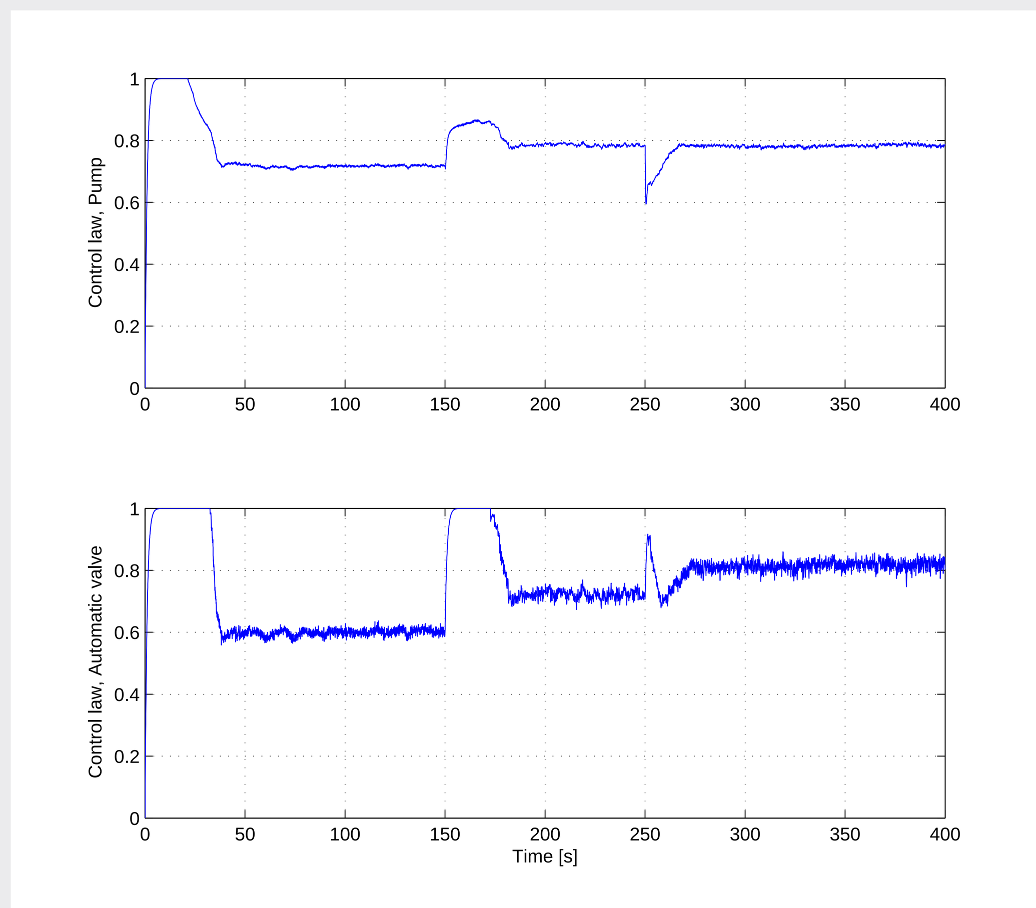
The NN-SANARX structure was trained with 2 neurons on the first and 10 neurons on the second sublayers, the linear and hyperbolic tangent sigmoid activation functions were chosen, respectively. Levenberg–Marquardt training technique was used.
The "Model based prediction" block was designed as extended Kalman filter, which can easily tackle the problems caused not only by network delay and visual signal processing on embedded system, but also caused by automatic valves.
In order to further minimize oscillations of the control signal, parameters of the neural network should be retuned (adapted) to reduced that particular discrepancy in the control law

$$\begin{aligned}J = \kappa_y \cdot \Big(\sum_{k=1}^{n}|v_{1k} - y_{1k}| + \sum_{k=1}^{n}|v_{2k} - y_{2k}|\Big) +\\ \kappa_u \cdot \Big(\sum_{k=1}^{n}|u_{r1k} - u_{1k}| + \sum_{k=1}^{n}|u_{r2k} - u_{2k}|\Big),\end{aligned} \qquad (6)$$

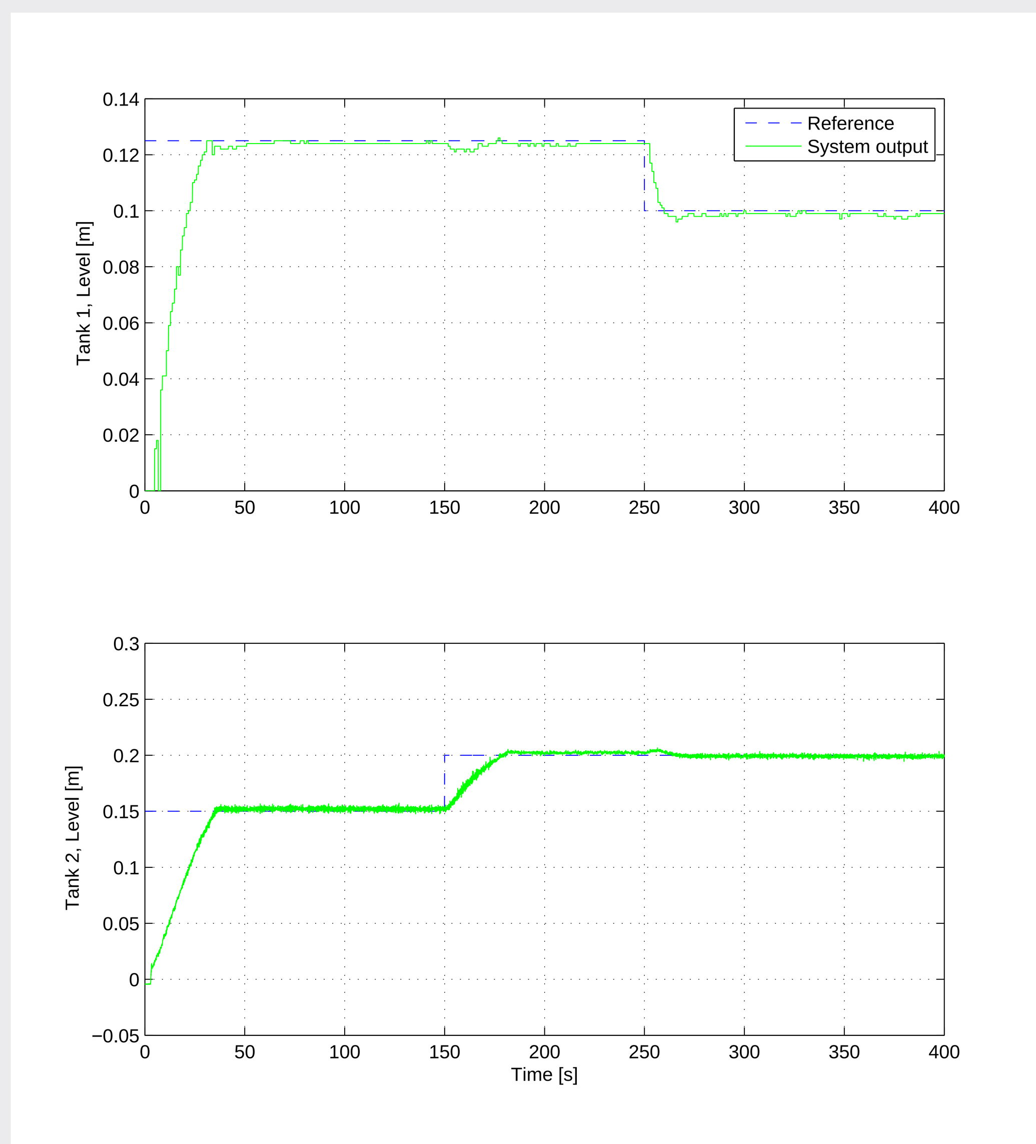
where κ_y, κ_u are weights for output and input signals, respectively. Difference between high frequency oscillations in the control law u and mean value of those u_r is considered. Dead zone for the automatic valve between tanks is very large, and it operates $u_2 \in [0.7, 1]$.

Control Results

The controller proposed in (5) with retuned parameters of the neural network was implemented to the system. The control signals for the pump and valve generated by the controller are the following



Liquid level control of the TITO system. Control system is capable of tracking reference signals for both tanks.



Acknowledgments

Study IT in .ee
sponsored by Skype