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Controller tunning for flow-through heater using artificial intelligence based on digital twin with recurrent neural networks

Krzysztof Żyła[1], Michał Frątczak[1*], Piotr Łaszczyk[1]

[1] Department of Automatic Control and Robotics, Silesian university of Technology, Akademicka 16, 44-100 Gliwice, Poland
* Corresponding author's e-mail: michal.fratczak@polsl.pl

ABSTRACT

The presented research results are related to the modelling and simulation of technological processes using recurrent neural networks (RNN). This paper presents the application of such modelling technique for a flow-through heater. The structure of the RNN was presented and the correctness of the obtained modelling results was verified. The application of such a model for the classical PI algorithm controller tuning was presented. The results were compared with the popular PI algorithm tuning rule (Chien-Hrones-Reswick). The advantage of the proposed approach to tuning controllers over traditional methods was pointed out.

Keywords: flow-through heater, recurrent neural network, LSTM, process modelling.

INTRODUCTION

Process dynamics modelling is one of the major fields of automatic control branch. Dynamic models are used for different purposes. The primary one is to obtain approximate but relevant information on process dynamic behaviour. These approximate models are generally used tune the controller properly (classical PI or PID) or even design control procedure (Model Base Predictive Control). Another application of Dynamic models is to build so called "Digital Twins" which are precise simulators of a given technological process. One should be aware that complexity of the model is usually related to model precision; however application of the model sometimes requires model complexity on a low level as for mentioned primary purpose of modelling. Classical approach to modelling uses first principle modelling that results in form of the model as a set of differential equations. This approach, however, requires a lot of knowledge and experience in the technology that are modelled. Even though first principle modelling does not result in high quality and model precision. The difficulty of such modelling approach usually lies in unrecognized phenomena and unknown values of parameters in first principle models. To rise the model precision, one should obtain the support of experimental data and make a compromise between knowledge based modelling and experimental based modelling [1]. However, modern techniques of modelling and technological progress in fast computing give the opportunity to develop and apply fully experimental models, which does not require much knowledge on technology used and phenomena existing in controlled process.

Modelling of dynamic systems appears to be one of the crucial issues in operating technological processes. There are different types of systems to be modelled e.g.: pneumatic, chemical, hydraulic, mechanic. One of the frequently type of systems that accompanies another technological processes is a thermal process [2–6]. Modelling of such processes has usually some amount of unrecognized phenomena (e.g. nonideal mixing) and uncertainty of some parameters (e.g. heat exchange coefficient). This makes first principle modelling inaccurate without any support of measurement data. Thus, it may be concluded that the more precise model is needed, the more experimental data is required. On the other hand, a well-prepared model can be used to design a control system and to create advanced control algorithms based on the object's model [7, 8]. One of the modern modelling techniques that is on the focus recently is based on artificial intelligence with application of recurrent neural networks (RNN). There are few research reports that show application of RNN in PID related issues [9] and ANN for tuning of PID algorithm [10, 11]. However, the approach proposed in this paper does not replace PID with AI technique or does not apply ANN as online supplement for PID control loop. The approach proposed in this paper applies RNN for control plant modelling and afterwards for tuning PID algorithm. RNN enables accurate modelling, even with limited knowledge of the internal structure of a modelled technological unit, relying solely on the provided input/output data. This approach of modelling is considered in presented research for modelling of flow-through (circulation) electric heater.

PROCESS DESCRIPTION AND MODELLING

An experimental setup with circulation electric heater was used to present applicability of considered methodology. The setup consists of the 6 kW heater supplied with water and accessories of two temperature sensors for inlet and outlet as well as flow sensor. Measurement equipment is wired to the analogue input module of Siemens Simatic S7-1500 PLC. Data logging is performed using application in Siemens WinCC Runtime environment with 100 ms cycle. The setup allows changing the power value of the heater using PWM hardware device. Thus, the power is expressed in this research as a percentage of maximal power of the heater that relates to the duty period in PWM modulator. Experimental data was collected at constant flow and randomly changed power of the heater. That set of data was used in training procedure for training the artificial neural network.

The access to experimental past data of modelled system is required to train artificial neural network. Traditional artificial neural networks (ANN) are design only to depict simple input-output relations where output depends only on current input data values. That type of artificial neural network does not able to retain past or historical information, because it does not any internal memory mechanism. That type of ANN might be successfully used to map an unknown physical relation or parameter values e.g. coefficients for first principle heat exchanger models [8]. However, it might be a challenging task for complex systems [9]. An alternative approach for ANN was proposed to cope with a demands for mapping not only static but also dynamic relations/ The recurrent neural networks (RNNs) achieve a memory through a local feedback loop (in the cell) or global feedback loop (for a whole network), which gives the opportunity to capture temporal dependencies in sequential data [10]. There are different types of RNNs depending on what information is relevant enough to be kept in the memory. In this research long-short-term-memory recurrent neural network (LSTM) is used, while it is capable to to capture long-term dependencies by handling the vanishing gradient problem in back propagation [11]. The LSTM defined for the purpose of this research is presented in the below figure (Figure 1).

As shown in the figure, the network has three inputs: the power P [%] of heating element, the flow of the water F [L/min], and the inlet temperature of water T_{in} [°C]. The input layer is used for normalizing these values to make further manipulation more suitable. The first fully connected layer captures possible relations and then outputs to the next LSTM layer, which is responsible for capturing long-term relations. The application of more than one LSTM layer is preferred [12] in this case, due to the complexity of the required data prediction and the typical use of large data sets for training as well as subsequent prediction. The last two layers are necessary to properly shape the

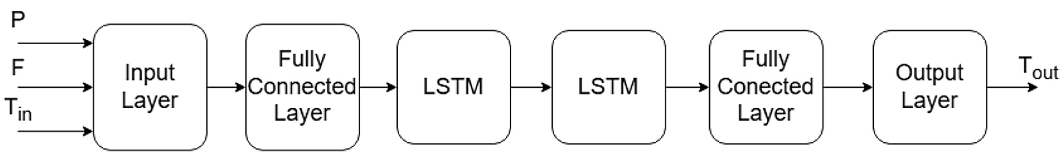

Figure 1. Scheme of neural network for circulation electric heater

output value that is the outlet water temperature T_{out} [°C], and to train the network for regression. Additionally, ReLU layers may be used at the input and output of the LSTM layers to additionally prevent the vanishing of gradients and improve the learning property of the network.

Any neural network has to be properly trained, to complete the modelling task using this methodology. The training data might be acquired from the real technological plant; however, this process is time consuming and sometimes expensive for the primary experiments with ANN structure and training process. To be time efficient, the training data were generated using very precise first principle model for this research. This model was developed in previous researches and supported with some experimental relations. This model was validated and its high quality was proven [13, 14]. This first principle model in time domain has a form of nonlinear differential equation (Equation 1) [10].

$$\frac{dT_{out}(t)}{dt} = \frac{F_{mod}(t)}{60\,V}\left(T_{in}(t) - T_{out}(t)\right) + \\ + \frac{P_{c,mod}(t)P_{max}}{100\,V\rho c_s} \tag{1}$$

where: V = 1.6 L – heater volume, P_{max} = 6000 J – maximal power of the heater, ρ = 1 kg/L – water density, c_s = 42000 kg/(J °C) is water specific heat capacity. $P_{c,mod}$ and F_{mod} are mapping additional dynamic relations and are presented in form of simple transfer functions (Equation 2–5).

$$P_{c,\mathrm{mod}}(s) = P_c(s)\frac{1}{1+5\,s}e^{-sT_{oP_c}} \tag{2}$$

$$T_{oP_c} = 9.7F^{-0.427} \tag{3}$$

$$F_{\mathrm{mod}}(s) = F(s)e^{-sT_{oF}} \tag{4}$$

$$T_{oF} = T_{oP_c} - 4 \tag{5}$$

Hence the model quality is proven, it allows rapid dynamic properties analysis at low cost without time and media consuming experiments. This model was used for experiments with neural network training, since it does not matter in this case the source of data for training. It was assume that if artificial neural network with a given structure is capable to map dynamic properties of the above first principle model, it can also map a real plant properties, even if some relations slightly differs from the physical model. Thus, for the tests with RNN training, a set of input-output data generated with the above high class model was used. It is worth noticing at this point that designing the above first principle model required knowledge of the technological unit structure and phenomena, while artificial neural network model is based on training data without such specific information as for model expressed by Equation 1–5. In other words, RNN models are more universal for many different processes whenever input-output data is accessible.

TRAINING PROCEDURE OF THE RNN MODEL AND VERIFICATION

Once the training data is collected, the model must be properly trained. This is where the number of neurons in each layer and additional settings matter. The number of neurons in the input and output layers are fixed and should be equal to the number of inputs and outputs, respectively. As for the internal layers, a different number of neurons has an impact on prediction quality. At this stage, it is worth noting that an excessive number of neurons can not only significantly affect the training procedure duration, but also cause over-fitting, resulting in poor quality predictions for cases that do not appear in training data. The MATLAB environment allows specifying additional training settings, such as the solver used, the gradient threshold (to prevent exploding gradient problem) or modifications to the training schedule for additional improvements.

To simulate this particular electric heater, each LSTM layer was designed with 500 neurons trained over multiple iterations. The root mean square propagation optimization algorithm [13] was chosen for its adaptive learning rate, which improves the learning efficiency of the neural network and enhances performance on time series or training data with significant measurement noise level. A piecewise learning rate was chosen to achieve variable learning rates throughout the training process. This approach allows faster retention of information at the beginning of training, which is then refined in later iterations. Additionally, the gradient was constrained to prevent the occurrence of gradient explosion.

A training data set was generated using first principle model, basing on the described above approach and assumptions. The input signals of power P and inlet temperature were changed in steps with respect to map different input values configuration and obtain the best representative data for training. Each step change of input generated respective time evolution change of the output temperature which was recorded. Thus, the output temperature time chart is a set of step change responses of the inputs. Figure 2 presents the time series generated in the described procedure. Once the network is trained for the mentioned number of iterations, it was used to predict the output value of the system based on the given time series of the inputs. In verification procedure the output of RNN model was compared with the output value of first principle model represented by Equations 1–5. Time series of the inputs generated for verification are different from the time series used for RNN training. The result of verification is shown in the Figure 3. Result shows that both outputs of RNN and first principle models are very close, thus it may be assumed that training procedure of RNN was successful and the RNN model depicts dynamics of the source object.

APPLICATION OF RNN FOR TUNING THE PID CONTROLLER

Once the network is trained, it might be used for different purposes. One of the application is to use it for building digital twin in simulation procedure. Another one that was considered is to use it for tuning the controller. The PID controller was considered in this case and the results of the proposed procedure were compared with one of popular tuning rule for this algorithm. In the previous section, it was proven that RNN with the proposed structure is capable to capture dynamic properties of the considered process (electric heater). In this case, the RNN was trained using new data set (Figure 4) assuming stable operating point of flow F = 2 L/min. constraining data set with such assumption makes the model quality higher for the chosen flow value. Training process gave positive results as for previous case with variable flow rate. The trained RNN was used then in controller tunig procedure. This procedure assumed searching for a pair of parameters of PI algorithm that minimizes an objective function J (Eq. 6). This objective function consists of MSE factor and additional cost function that penalizes overshooting.

$$J = \frac{1}{N}\sum_{i=1}^{N}\left(y_{set}(i) - y(i)\right)^2 + \\ + (\max(y_{set}) - \max(y))^2 \tag{6}$$

where: y_{set} – setpoint value, y – process output value, N – number of discrete time instances (samples).

The possible space of PI tuning parameter combination (gain and integral time) was searched to minimize objective function

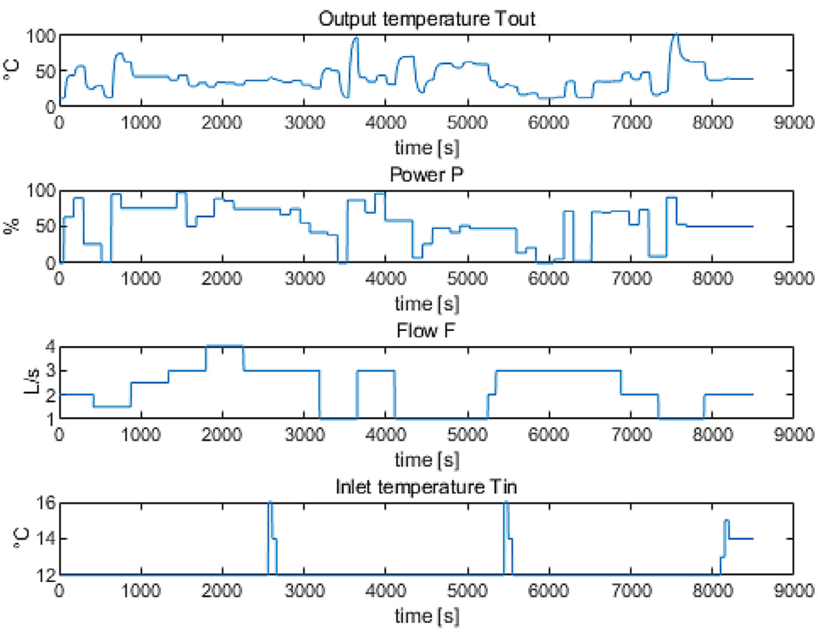

Figure 2. Data set generated for RNN training

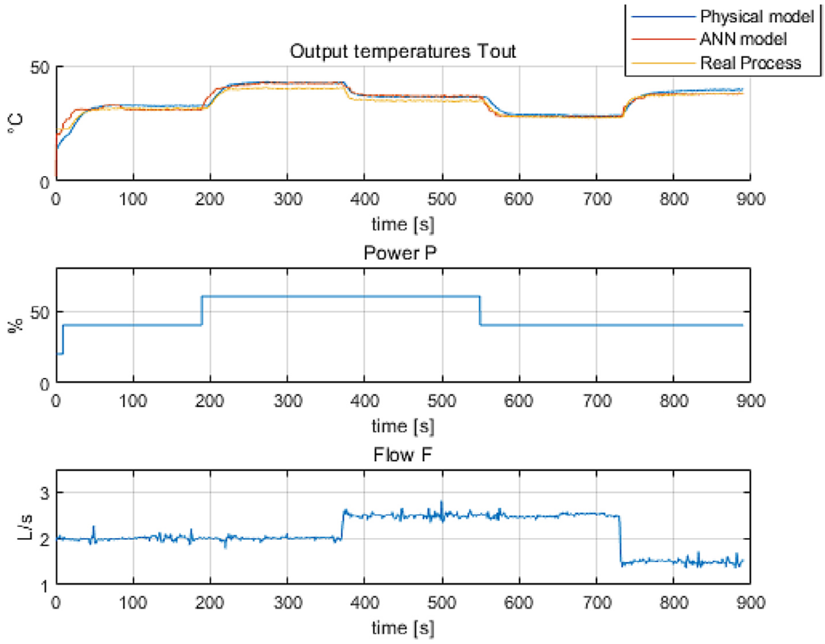

Figure 3. Output prediction comparison between RNN and physical model, compared to real output

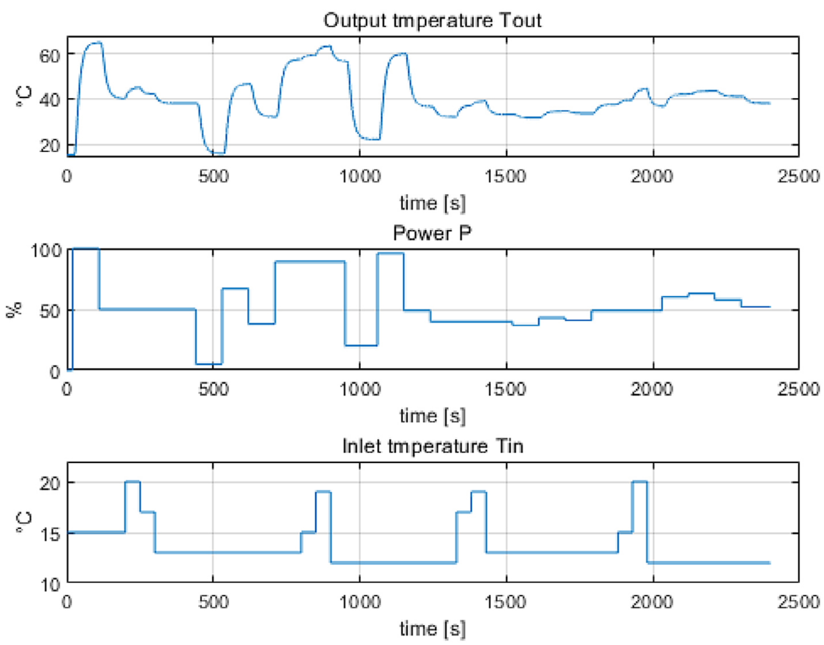

Figure 4. Data set for training RNN used for PI algorithm tuning procedure

represented in Equation 6. Schematic representation of this idea is presented in Figure 5. Sample results for objective function J values and different PI parameter combinations are presented in Figure 6. PI controller tuning parameters were compared with the one calculated using one of the most popular Chien-Hrones-Reswick (CHR) tuning rule [14, 15]. In this case, the CHR rule was chosen with the option for fast settling time and limit for overshooting. That option is likely compatible with the demands defined for tuning procedure with RNN and objective function defined in Equation 6. Results of both PI algorithm tuning approaches are presented in Table 1. In the next step, the PI controller performance was compared with both set of tuning parameters (Figure 7). For comparison of controller performance J objective function in both cases was calculated (Table 2).

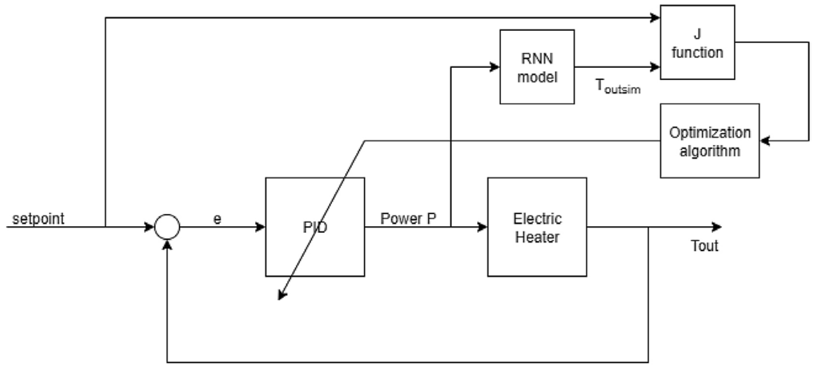

Figure 5. Schematic diagram of the PID controller tuning system using a RNN model

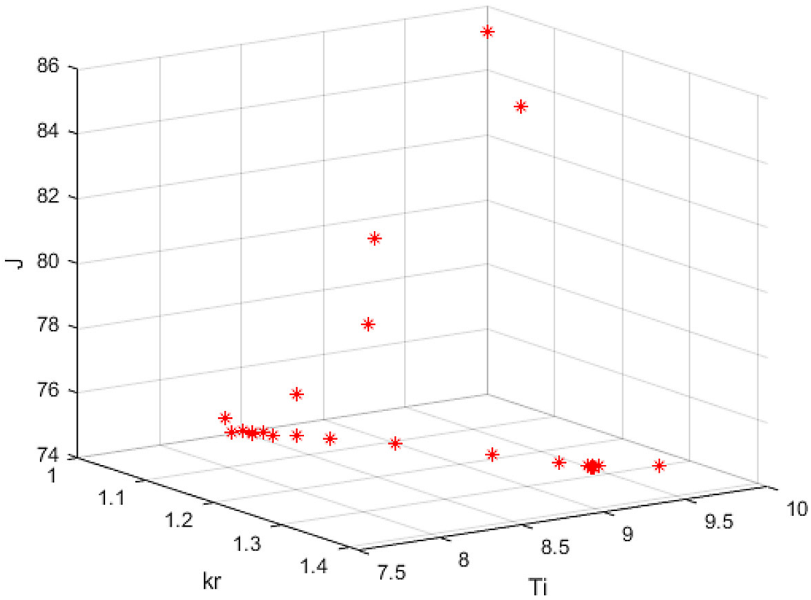

Figure 6. Sample objective function J values with different PI parameters

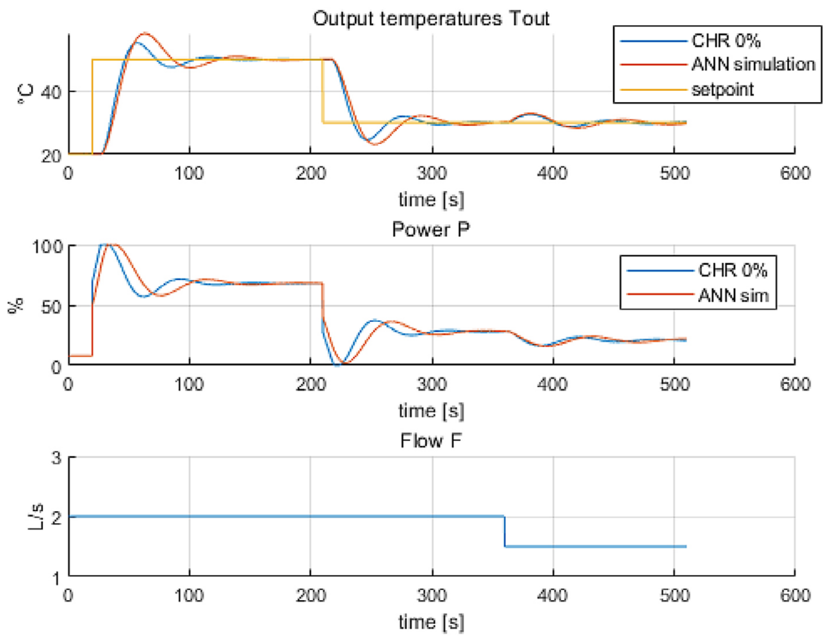

Figure 7. Result of experiment with PID controller tuned with CHR rule and using RNN simulation

Table 1. Comparison of PI tuning results

Tuning procedure	Kr [°C/%]	Ti [s]
CHR	2.02	13.1
RNN	1.38	9.1

Table 2. Comparison of quality functions

Parameter	J
RNN	66.63
CHR	113.31

CONCLUSIONS

The proposed approach for PI algorithm tuning with artificial neural networks gave positive results that are comparable to classical methods for tuning that algorithm. Although this procedure requires designing RNN network structure, in some aspects it is more convenient in application than classical tuning rules. The main advantage of the proposed tuning procedure is that it is time efficient and requires minimal initial setup. The object dynamics adaptation ability is based solely on collected I/O measurements, thus it does not require any prepared experiment and can be based on any historical data stored in the monitoring system of a given technological process. In the paper proposed structure of RNN was used to predict the output temperature of circulating heater. Good quality of the model based on artificial intelligence was proved.

The proposed PI algorithm tuning procedure might be very useful in the case where the process is constantly disturbed and any experiment with step response to manipulated value can be problematic if not impossible. The only drawback is that RNN requires some time for learning on the basis of the data set acquired from the technological process. This procedure might be used in the cases when the process is tuned for the first time or for the process with poorly tuned controller as well with a little interference to the technological process flow.

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