Adaptive neurofuzzy predictive control of nuclear steam generators

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Abstract. The main emphasis of this paper is the application of adaptive neurofuzzy model-based predictive control, to regulate the water level in the U-tube steam generating (UTSG) unit used for electricity generation. A nonlinear predictive controller is designed on the basis of a Takagi-Sugeno fuzzy model with B-spline membership function. By on-line adaptation of the neurofuzzy model, improvement of the control performance can be achieved with the time-variant process behaviour. For this purpose, a normalized least-square algorithm is utilized which exploits the local linearity of Takagi-Sugeno fuzzy models. An optimization approach with a quadratic programing technique is used to calculate predictions of the future control actions. The effectiveness and real-world applicability of the proposed approach are demonstrated by computer simulation. The control experiments were successfully conducted for this nonlinear process with satisfactory results and performances.

Key words: neurofuzzy model • predictive control • U-tube steam generator

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Introduction

The water-level regulation of UTSG is a very difficult control problem. The difficulty arises due to reasons such as nonlinearity of dynamics, high complexity, time varying and non-minimum phase dynamics (also known as reverse dynamics), and unreliable sensor feedback at low power [14]. Therefore, UTSG plants are controlled using constant-gain proportional-integral (PI) controllers, at high power operations. At low power operations (less than 20% of the nominal power), water level cannot be maintained properly with the PI controller due to the thermal effects of UTSG and the uncertainty in measured values of the feedwater and steam flow rate. Hence, the level control is performed manually at low powers. Even with a skilled team of operators, the rate of incidents due to manual control could not be neglected. So, a need for the performance improvement in the existing water level regulators is obvious.

Many advanced control methods such as adaptive predictive control [11, 12]; fuzzy logic control [8], model predictive control [7, 11]; optimal control [9] and combination of these control methods [10, 13] have been suggested to resolve the (UTSG) water level control problem. In spite of the many advanced control methods proposed, operators are still experiencing difficulties especially at low powers.

One of the powerful tools for controlling industrial process systems is MPC [2–4] which refers to the direct use of an explicit and separately identifiable model to control an industrial process. All model predictive control (MPC) algorithms are based on the moving horizon approach known as the open-loop optimal feedback control approach. In this method, an identified process model predicts first the future response; the current control action is then determined so as to obtain the desired performance over a finite time horizon. This method has many advantages over the conventional infinite horizon control, because it easily handles the input and output constraints in a systematic manner during the design and implementation of the controller.

Since steam generator is a nonlinear system, the linear MPC algorithm [2, 4], may not result in a satisfactory dynamic performance. Some nonlinear model predictive control (NMPC) algorithms have been developed [5], these algorithms accept various kinds of nonlinear models such as nonlinear ordinary differential algebraic equations, partial differential algebraic equations and delay equation model. Such models can be accurate over a wide range of operation conditions; however, they are impractical for many industrial problems. Moreover, an NMPC that incorporates a nonlinear model may require tremendous computational effort for optimization; this consequently may disqualify NMPC for on-line applications. If a nonlinear process can be precisely described by a set of linear sub-models in someway such as Takagi-Sugeno (TSK) fuzzy model, then the design of a model predictive controller can be greatly simplified.

A novel modelling methodology based on fuzzy logic is introduced by Takagi and Sugeno in [16]. In this methodology a nonlinear system is divided into a number of linear or nearly linear subsystems. A quasi-linear empirical model is then developed by means of fuzzy logic for each subsystem. The model is a rule-based fuzzy implication. The whole process behaviour is characterized by a weighted sum of the outputs from all quasi-linear fuzzy inference systems. This methodology facilitates the development of a number of quasi-linear models regulated by fuzzy computations. It also provides an opportunity to simplify the design of model predictive controller.

In this paper, Takagi-Sugeno modelling methodology is used to generate a fuzzy convolution model for U-tube steam generator. Consequent parameters of this model are updated on-line with a recursive parameter estimation algorithm called as weighted recursive least square (WRLS) [6]. Then, this fuzzy model and a predictive control method, which is called constrained receding horizon predictive control (CRHPC), is used to solve the steam generator water level control problem. The proposed controller has been applied to a nonlinear model of steam generator taken from [1, 15] to verify its real performance.

UTSG model and the water level control problems

UTSG model

A pertinent UTSG model is desired to give physical ideas about the steam generating (SG) dynamics and be used as a simulator to replace actual plant testing for early evaluation of the controller. UTSG is a highly nonlinear, unstable and multivariable thermal-hydraulic process system. The three outputs of a UTSG which are usually measured are the water level $y = L_w$, the cold-leg temperature T_{cl}, and the secondary steam pressure P_{sat}. The five disturbances acting upon the system are the hot-leg temperature T_{hl}, the primary pressure P_{pr}, the primary mass flow rate q_{pr} (always a constant within small random variations), the feedwater temperature T_{fw}, and steam flow rate $v = q_{st}$. Changes in the power demand are translated to changes in the UTSG steam flow rate and this signal provides the persistent excitation needed for effective system identification. The hot-leg temperature and the feedwater temperature are usually expressed as functions of the operating power, and given the current operating power level they can all be calculated in a straightforward manner. The feedwater flow rate $u = q_{fw}$ is the only control input to the UTSG.

A UTSG simulator developed by Strohmayer in [15] and modified by Choi in [1] is adopted for the purpose of this work. The simulator was developed using a one-dimensional mass momentum and energy conservation equations. An integrated secondary recirculation-loop momentum equation has been incorporated into the simulator to calculate the water level. Figure 2 shows a block diagram of the UTSG simulator with the inputs, disturbances, and outputs and the PI control structure.

Control problems in low power operation of UTSG

The water level of the UTSG should be maintained within its lower and upper limits. Failure to maintain water level would lead to the following serious consequences, including unintended plant shutdowns and system damage [14]:
– If the low water level exposes the U-tubes, the heat transfer from the primary circuit to the secondary circuit will not take place efficiently. Consequently, primary circuit builds-up heat within itself, which causes the reactor to trip off.
– If the water level rises too high, the steam will contain more moisture (dryness < 99.9%). And the wet steam may damage the turbine blades; therefore, turbine trips off.

Thus, it is extremely important that the water level of the UTSG be regulated within its limits. At present, a significant percentage of plant shutdowns and system unavailability are reportedly due to failures in UTSG water level control [7]. For the UTSG in a NPP, the main goal of control system is to maintain the water level at a desired value by regulating the feedwater flow rate. In general, there are several reasons that make control of the UTSG water level difficult. These issues can be summarized as follows:
– The UTSG is an open loop unstable system.
– The plant dynamics are highly nonlinear. This is reflected by the fact that the linearized plant model shows significant variations with operating power.
– The thermal effects, known as shrink and swell phenomena, add to the complexity of the control problem because it tends to mislead simple feedback controllers.
– A problem in the water level control is the limited amount of feedwater flow available for control. Reverse flow is not possible and feedwater flow could

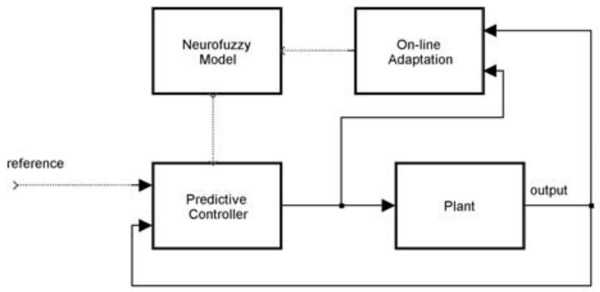

Fig. 1. Structure of the control system.

not be higher than the pump rating. So, there is an explicit limitation in the magnitude of the control signal.
– The most critical and widely used feedback signals are steam flow rate and feedwater flow rate. It is more often the case that these signals are not accurate enough during start-up transients, and at low power operations. Under these conditions, flow rates are small in magnitude, and the process noise corrupts them beyond the limit of being useful feedback signals.

Control system strategy and structure

The control structure consists of two main parts: a dynamic fuzzy model, which calculates the predictions of the process outputs and works as a predictor, and a controller, which optimizes the process by minimizing the cost function and works as a predictive controller. The predictive fuzzy model can be developed by the Takagi-Sugeno fuzzy technique and can be taken as a collection of many linear models. Figure 1 represents the structure of the fuzzy model based predactive control (FMBPC) system.

The simplest and most widely used approach for modelling nonlinear dynamics using TSK fuzzy model is extending the ARX model to form the so-called Nonlinear Auto Regressive with EXogenous inputs (NARX) model,

$$y(t) = f(x(t)) \tag{1}$$

where the element of the regression vector $x(t)$ is given by:

$$x(t) = [y(t-1), y(t-2), \dots, y(t-m), u(t), u(t-1), \dots, u(t-n+1)] \tag{2}$$

They are composed of previousce m process outputs and previous n process inputs and their numbers depend on the process complexity.

Throughout this contribution, the unknown nonlinear function f can be approximated by Takagi-Sugeno type fuzzy rules. The rule base comprises a collection of N rules of the form:

$$R^{(r)}: \text{if } x_1 \text{ is } X_1^{(r)} \text{ and } x_2 \text{ is } X_2^{(r)}\ x_p \text{ is } X_p^{(r)} \text{ then } f^{(r)}(x) = a_r^T x \tag{3}$$

For identification of UTSG behaviour based on input-output data, we used a TSK fuzzy model and a subtractive clustering method (off-line identification). The identification signals were considered at different powers.

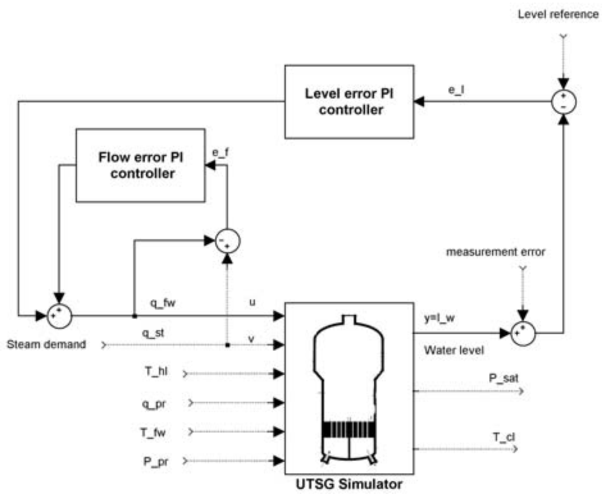

Fig. 2. Block diagram of the UTSG simulator and PI control structure.

To start the identification of the UTSG model, first the level control is stabilized by means of two PI controllers, one for the level error control and another one for the flow error control, using these tow controllers it is possible to regulate the water level at all specific power levels. The structure of the two PI controllers is shown in Fig. 2.

Using this PI control structure, a prolonged simulation of the UTSG plant was carried out using a sampling interval of 1 s. Starting from the beginning of the simulation, the reference water level was intentionally changed in 0.5 cm steps in every 300 s time intervals, over the entire range of $20 \to 24 \to 16 \to 10$ cm, which takes 5100 s in total. Then, another 2 h was given for random reference changes.

At all times, random steam disturbances were introduced, the disturbance is formed by the addition of a pseudo random binary sequence (PRBS) and a white noise. The results of simulation under PI control at power level 50% are shown in Fig. 3.

Similar data were obtained for all specific power levels, these data were collected in a sequence of 61 500 samples, a set of 43 500 samples formed from the first 8700 samples of each power level data, are used to train a TSK fuzzy model of the system. The remaining 18 000 samples are used as validation set. The regression vector as in Eq. (2) was chosen using the following parameters, $m = 2, n = 2$.

$$x(t) = [y(t-1), y(t-2), u(t), u(t-1), p(t)]$$

where $p(t)$ is the operating power level, estimated from the steam flow rate. The identified fuzzy model consists of 80 rules and has five inputs, they are four elements of the regression vector and the power level and one output. The linear parameters of this fuzzy model are adapted at each sample time (on-line adaptation). For this purpose, we use nonlinear least min square (NLMS) algorithm with learning rate η, that is equal to 0.98. The on-line adaptation of the fuzzy model takes about 0.2 s on a Intel® Core™2 Due CPU 2.66 GHz--1.96 Gb of Ram.

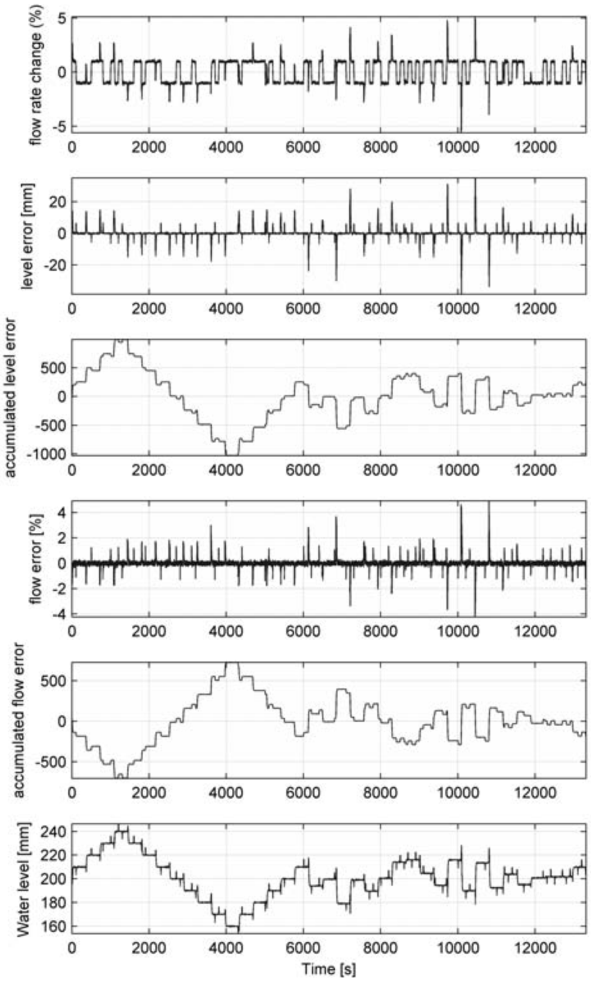

Fig. 3. Simulation under PI control at 50% power level. The first subplot shows the percent of feedwater flow rate change with respect to nominal value, the second subplot shows the error between water level reference and water level, integral of this error is shown in the third subplot. In the forth and fifth subplot, the difference between feedwater flow rate and steam flow rate and the integral are shown.

The predicted output using fuzzy model $y(t+k|t)$ for $k = 1, \ldots, N_p$ depends on the input and output values up to time t and the future control signals $u(t+k|t)$ and these are the values to be calculated. The objective of the controller is to keep the output $y(t)$ as close as possible to a set-point $r(t)$. A general objective function is the quadratic form, mostly referred to as generalized predictive control (GPC) [3], the cost function used to evaluate the "distance" between the reference and the output makes use of a quadratic norm:

$$(4)\quad J = \sum_{k=1}^{N_p} (r(t+k\,|\,t) - y(t+k\,|\,t)^2 + \rho \sum_{k=1}^{N_c} \Delta u(t+k-1\,|\,t)^2$$

where $\Delta u(t) = u(t) - u(t-1)$ is the incremental control action, ρ is a weighting factor penalizing changes in the control actions. Once the optimal sequence is calculated, only the $u(t|t)$ signal is implemented, for time $t+1$ a new value of y is measured and a new input sequence is calculated.

Then, the objective function J, can be written in a quadratic programing form and solved in MATLAB by using the quadprog.*m* function in the optimization toolbox.

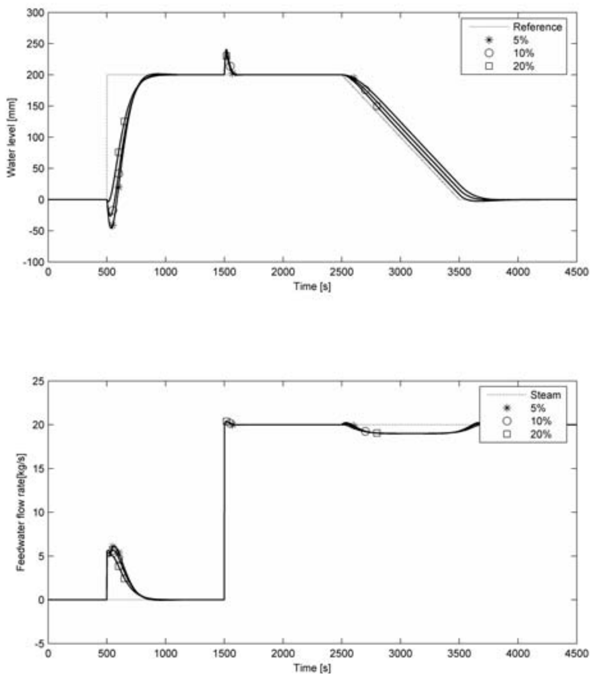

Fig. 4. Performance of proposed controller (low power).

Implementation of the controller and performance results

After some "trial and error" experimentation, the prediction horizon, control horizon and delay are chosen 30, 20 and 3, respectively and $\rho = 10^{-2}$. The computation time of the control action was 0.5 s on a Intel® Core™2 Due CPU 2.66 GHz-1.96 Gb of Ram.

Figure 4 shows the water level variations for powers levels of 5, 10 and 20%. The results easily approve high capability of the proposed control for this tracking problem. This became more highlighted for lower power levels in which non-minimum phase behaviours of the steam generator are more observable. Furthermore, the proposed controller can still follow the desired trajectory for changes in power levels; this indicates how robust the controller is. The control signal is shown in Fig. 4. Figure 5 shows the performance of the proposed controller at high powers, when the set-point (water level) and the steam flow rate change. These results indicate that the proposed controller has a good performance for tracking the set-point at high power level, too. As observed in Figs. 4 and 5, the amount of control efforts will increase as the power levels decrease. These figures show that system has a non-minimum-phase behaviour in low powers. Figure 6 compare the performance of the proposed controller and conventional PI controller optimized by a genetic algorithm [10] at power levels of 5%. The proposed controller shows better performance under the step and ramp change of power.

Conclusions

In this work, an adaptive fuzzy model based predictive controller was developed to control the water level of nuclear steam generators. In this algorithm, a local linear fuzzy model of the steam generator is tuned at

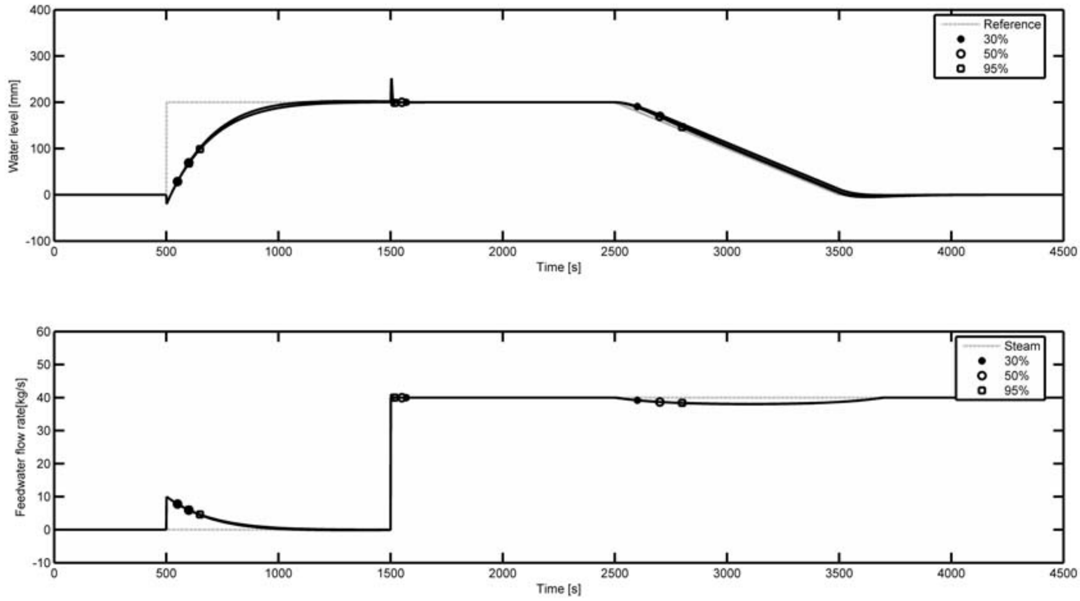

Fig. 5. Performance of proposed controller (high power).

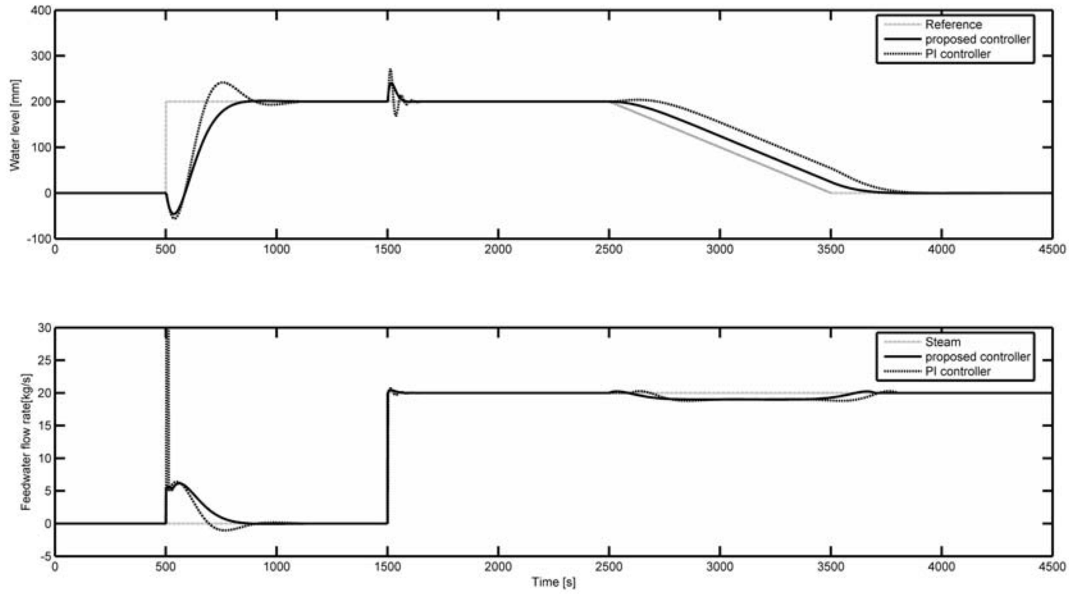

Fig. 6. Comparison of the proposed controller and PI controller for UTSG at 5% power.

each time step, based on a TSK fuzzy model and a recursive estimation algorithm to design a model predictive controller. Computer simulations show, the proposed controller has a good performance for tracking the step and ramp reference trajectory and has a good performance against the steam flow rate change. The proposed controller was compared to the PI controller and was known to have a better performance.

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