Wavelet network controller for nuclear steam generators

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Abstract. Poor control of steam generator water level is the main cause of unexpected shutdowns in nuclear power plants. Particularly at low powers, it is a difficult task due to shrink and swell phenomena and flow measurement errors. In addition, the steam generator is a highly complex, nonlinear and time-varying system and its parameters vary with operating conditions. Therefore, it seems that design of a suitable controller is a necessary step to enhance plant availability factor. The purpose of this paper is to design, analyze and evaluate a water level controller for U-tube steam generators using wavelet neural networks. Computer simulations show that the proposed controller improves transient response of steam generator water level and demonstrate its superiority to existing controllers.

1. Introduction
One of the most important factors that indicate the economic performance of a power plant is its availability. Plant availability is defined as the fraction of time a power plant is available for electricity generation during a given period [1]. The advantage of a nuclear power plant (NPP) over a fossil power plant is low operating cost, so the plant availability is a key factor to economic index of an NPP. Therefore, economic feasibility of an NPP requires smooth and uninterrupted plant operation during electrical power demand variations.

Water level control of steam generator (SG) is an important problem that must be considered for plant safety and availability. Poor control of the SG water level can lead to frequent reactor shutdowns. About 25% of emergency shutdowns in the nuclear power plants based on pressurized water reactor (PWR) are caused by poor control of the SG water level at low powers [1]. Such shutdowns can decrease the plant availability greatly and must be minimized.

Currently, constant-gain PI controllers are used in nuclear utilities for SG water level control at high power operations. At low power operations (less than 20% of the nominal power), water level cannot be maintained properly with PI controller due to the thermal effects of SG 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 methods have been suggested to resolve the SG water level control problems. Irving et al. presented a linear model with varying parameters to describe the U-tube steam generator (UTSG) dynamics over the entire operating power range. Then they proposed a model reference adaptive PID controller [2]. Design of suboptimal controller using linear output feedback control has been reported by Feliachi and Belbelidia [3]. Choi et al. proposed a PI-type controller that uses an observer to estimate the UTSG water inventory [4]. Na and No designed an adaptive observer-based controller [5] and Na presented a UTSG water level controller based on the estimation of flow errors.
A more general gain-scheduled linear quadratic Gaussian with loop transfer recovery (LQG/LTR) controller using a linearized version of a nonlinear validated model of the SG is proposed by Menon and Parlos [7]. Water level control systems based on fuzzy logic have been reported in numerous references. Steam generator water level controller using fuzzy logic has been actually installed at the Fugen NPP [8]. Cho and No presented a neurofuzzy controller, which is implemented using a multilayer neural network with special types of fuzzifier, inference engine and defuzzifier [9]. A robust fuzzy gain-scheduler designed by Cho and No, based on the synthesis of fuzzy inference and $H_{\infty}$ technique [10]. Na, presented a fuzzy controller which is tuned off-line with genetic algorithms using water level, feedwater and steam flow rate signals [11]. Kim et al. proposed a gain-scheduled controller with guaranteed $L_2$ performance [12]. Kothare et al. presented a controller based on an extension of model predictive control principle [13]. A gain-scheduled $H_{\infty}$ controller has been designed for UTSG by Parlos and Rais [1]. Na, presented an auto-tuned PID controller using a model predictive control method [14]. A novel architecture for integrating neural networks with industrial controllers was proposed by Parlos et al., for use in predictive control of SG [15]. In the proposed method a PI controller is used to control the process and a recurrent neural network models the process as a multistep-ahead predictor to. Na et al. designed an adaptive predictive controller. A recursive parameter estimation algorithm estimates unknown parameters of the mathematical model of steam generator. This model is then used to design a generalized predictive controller [16]. Finally, Habibiyan et al. proposed a controller based on neural feedback linearization technique. A simple fuzzy system was used as gain-scheduler to overcome dependency of controlled system behavior on power [17].

In spite of many advanced control methods proposed for the control of nuclear SG water level, operators are still experiencing difficulties especially at low powers. Therefore, it seems that a suitable controller to replace the manual operations is still needed.

Neural networks have been applied successfully in the identification and control of dynamic systems. For a systematic classification of neural networks-based control, the reader is referred to a survey by Agarwal [18]. The universal approximation capabilities of the multilayer perceptron (MLP) make it a popular choice for modeling nonlinear systems and for implementing general-purpose nonlinear controllers.

As wavelet has emerged as a new powerful tool for representing nonlinearity, a class of networks combining wavelets and neural networks has recently been investigated. It has been shown that wavelet networks provide better function approximation ability than the multilayer perceptron and radial basis function (RBF) networks.

In this paper, a wavelet network based on feedback linearization technique is used to the UTSG water level control. At 5% power, we will use the approximate wavelet NARMA-L2 model to identify the UTSG. Then local wavelet network controller will be simply obtained by rearrangement of neural network plant model, which has been trained off-line, in batch form.

The remainder of this paper is organized as follows: in section 2, the water level control problems and a mathematical model for UTSG are presented. In section 3, wavelet network based on feedback linearization control method is discussed. Section 4, presents the computer simulation and the comparative result with respect to a well-tuned PI controller. The summary and conclusion are given in section 5.

## 2. The water level control problems and U-tube steam generator model

### 2.1. Control problems in low power operation of UTSG

Steam generators in PWR plants, transfer heat from a primary coolant system (pressurized water) to a secondary coolant system. Primary coolant water is heated in the core and passes through the SG,
Figure 1. (a) General view of a PWR power plant and (b) schematic of a UTSG.

where it transfers heat to the secondary coolant water to make steam. The steam then drives a turbine that turns an electric generator. Steam is condensed and returns to the SG as feedwater. A general schematic view of a PWR plant is shown in figure 1a. Two types of water level measurements are provided, as shown in figure 1b: narrow range level (NRL) and wide range level (WRL).

Figure 2 shows the responses of the narrow range water level to steps in feedwater and steam flow rates at different operating powers. To generate the responses, we have used the power-dependent linear model identified by Irving et al. [2].

For the SG in an NPP, the main goal of control system is to maintain the narrow range 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 not be higher than the pump rating. So, there is an explicit limitation in the magnitude of the control signal.

2.2. U-tube steam generator model

Usually, both the controller design and the resulting controller performance on the actual plant strongly depend on the accuracy of mathematical model used to describe the plant. However a highly accurate model is generally highly complex and nonlinear, and therefore leads to difficulties in controller design. Detailed theoretical models for the UTSG, based on fundamental conservation equations and thermodynamic principles are typically used prior to plant licensing for simulating accident conditions [19], for operator training [20] and to validate controller performance prior to implementation on the plant [7]. These models, unfortunately, are too complex for use in controller design.

A pertinent SG model is desired to give physical ideas about the SG dynamics and be used as a simulator to replace actual plant testing for early evaluation of the controller. A model, which has been widely used in UTSG modeling for control purposes is the linear parameter-dependent model presented in [2].
Figure 2. Responses of the narrow range water level at different operating powers (indicated by %) to: (a) a 0.4% step in feedwater flow rate; (b) a 0.4% step in steam flow rate.

The transfer function relating the feedwater flow rate, $Q_e$, and the steam flow rate, $Q_v$, to the narrow range water level, $Y$, is given by

$$Y(s) = \frac{G_1}{s} - \frac{G_2}{1 + \tau_2 s}(Q_e(s) - Q_v(s)) + \frac{G_3 s}{\tau_1^{-2} + 4\pi^2 T^{-2} + 2\tau_1^{-1} s + s^2} Q_e(s)$$  \hspace{1cm} (1)

where $s$ is the Laplace variable, $\tau_1$ and $\tau_2$ the damping time constants, $T$ the period of the mechanical oscillation, $G_1$ the magnitude of the mass capacity effects, $G_2$ the magnitude of the shrink and swell phenomena and $G_3$ magnitude of the mechanical oscillation.

In (1), all constants are positive. $G_1 / s$ is the mass capacity effect of the UTSG. It integrates the flow difference, $(Q_e(s) - Q_v(s))$, to calculate the change in water level. In all operating powers, $G_1$ is equal to 0.058 mm/kg. $-G_2 / (1 + \tau_2 s)$ is the thermal negative effect caused by the shrink and swell phenomena, which appear initially in the case of feedwater or steam flow rate changes. The last term is the mechanical oscillation effect caused by the inflowing feedwater to the UTSG. The wide range water level is given by

$$WRL(s) = \frac{G_1}{s} (Q_e(s) - Q_v(s)).$$

From the responses shown in figure 2, we see that the dynamics of the UTSG change with operating power. This is reflected in the above model by allowing the parameters $G_2$, $G_3$, $\tau_1$, $\tau_2$, and $T$ to be power-dependent. The model parameters at different powers have been identified from experimental data [2] and are given in table 1 for 5% of nominal power.

3. Wavelet network controller based on feedback linearization technique

3.1. Neural feedback linearization control

The neurocontroller described in this section is referred to by two different names: feedback linearization control and NARMA-L2 control. It is referred to as feedback linearization when the plant model has a particular form (companion form) and as NARMA-L2 control when the plant model can be approximated by the same form. Linearization by feedback is a promising approach for the control of nonlinear systems [22]. The main idea is to transform a state space model of the plant into new
The first step in order to use NARMA-L2 control is to identify the system to be controlled. One standard model that has been used to represent general discrete-time nonlinear systems is the nonlinear autoregressive-moving average (NARMA) model

\[ y(k+d) = F[y(k), y(k-1), ..., y(k-m+1), u(k), u(k-1), ..., u(k-n+1)] \]

where \(u(k)\) is the system input, \(y(k)\) is the system output and \(d\) is the relative degree (see [26] for more details). Multilayer neural networks can be used to identify the function \(F[\bullet]\). Denoting the network mapping by \(N[\bullet]\), the identified model has the form

\[ \hat{y}(k+d) = N[y(k), y(k-1), ..., y(k-m+1), u(k), u(k-1), ..., u(k-n+1)] \]

where \(\hat{y}(k+d)\) is the estimate of \(y(k+d)\). Identification is carried out at every instant \(k\) by adjusting the parameters of the neural network using the error \(e(k) = \hat{y}(k) - y(k)\).

We want the system output to follow some reference trajectory, \(y(k+d) = y_r(k+d)\), so the next step is to obtain the control input \(u(k)\). Since the relative degree \(d\) exists, the system is necessarily controllable and \(\partial F/\partial u(k) \neq 0\) along the trajectory [26]. Hence, it follows from the implicit function theorem that \(u(k)\) can be expressed as

\[ u(k) = G[y(k), y(k-1), ..., y(k-m+1), y_r(k+d), u(k-1), ..., u(k-n+1)] \]

where \(G: \mathbb{R}^{m+n} \rightarrow \mathbb{R}\) and \(G \in C^\infty\). The control problem is consequently to determine (or estimate) the map \(G\) from the measured values of inputs and outputs as well as the given reference signal \(y_r(k+d)\). Since the controller is in the feedback loop of a dynamical system, the adjustments of the parameters of a neural network used to approximate \(G\) cannot be carried out using static back propagation. Besides, dynamic back propagation is quite slow and computationally intensive. One solution proposed by Narendra and Mukhopadhyay is to use approximate models to represent the system [26]. These models have been applied at Yale University to a variety of control problems. Extensive simulation studies have shown that the neural controllers designed using approximate models perform very well, and in many cases even better than an approximate controller designed using the exact NARMA model.

The controller described in this section is based on the NARMA-L2 approximate model, which uses a Taylor expansion of \(F[\bullet]\) around the scalar \(u(k)\). The model is given by

\[ y(k+d) = f[y(k), ..., y(k-m+1), u(k-1), ..., u(k-n+1)] + g[y(k), ..., y(k-m+1), u(k-1), ..., u(k-n+1)] \cdot u(k). \]

This model is in companion form, where the next control input \(u(k)\), is not appeared in the nonlinear functions \(f\) and \(g\). The advantage of this form is that we can solve for the control input that causes the system output to follow the reference signal: \(y(k+d) = y_r(k+d)\). The resulting controller would have the form

Table 1. Parameters of a steam generator linear model at 5% of nominal power.

| Power Level (%) | G_2 (mm/sec/kg) | G_3 (mm/kg) | \(\tau_1\) (sec) | \(\tau_2\) (sec) | T (sec) | \(Q_e\) (kg/sec) |
|-----------------|-----------------|-------------|-----------------|-----------------|--------|-----------------|
| 5               | 9.63            | 0.181       | 41.9            | 48.4            | 119.6  | 57.4            |
Using this equation directly, causes a realization problem, because we must determine the control input, \( u(k) \), based on the output at the same time, \( y(k) \). So, instead, we use the model
\[
y(k+d) = f\{y(k), \ldots, y(k-m+1), u(k), \ldots, u(k-n+1)\} + g\{y(k), \ldots, y(k-m+1), u(k), \ldots, u(k-n+1)\} \cdot u(k+1).
\]

Using (2) we can obtain the controller
\[
u(k+1) = \frac{y_r(k + d) - f\{y(k), \ldots, y(k-m+1), u(k), \ldots, u(k-n+1)\}}{g\{y(k), \ldots, y(k-m+1), u(k), \ldots, u(k-n+1)\}} \tag{3}
\]
which is realizable for \( d \geq 2 \).

\subsection{3.2. Wavelet networks}

Wavelet is a new powerful tool for representing nonlinearity \cite{27}. A function \( f(t) \) can be represented by the superposition of daughters \( h_{a,b}(t) \) of a mother wavelet \( h(t) \), where \( h_{a,b}(t) \) can be expressed as
\[
h_{a,b}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right)
\]
a and \( b \) are, respectively, called dilation and translation parameters.

The continuous wavelet transform of \( f(t) \) is defined as
\[
w(a,b) = \int_{-\infty}^{\infty} f(t) h_{a,b}(t) \, dt
\]
and the function \( f(t) \) can reconstructed by the inverse wavelet transform
\[
f(t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} w(a,b) h_{a,b}(t) \, da \, db \tag{4}
\]
The continuous wavelet transform and its inverse transform are not directly implementable on digital computers. When the inverse wavelet transform (4) is discretized, \( f(t) \) has the following approximative wavelet-based form.
where the $w_k$, $b_k$ and $a_k$ are weight coefficient, translations and dilations for each daughter wavelet. This approximation can be expressed as the neural network of figure 3, which contains wavelet nonlinearities in the artificial neurons rather than the standard sigmoidal nonlinearities.

The wavelet network (5) can only be used to approximate single-input single-output (SISO) functions. We can use a model of neural network with $N$ inputs as suggested in (6)

\[
\hat{f}(t) = \sum_{k=1}^{K} w_k h\left(\frac{t - b_k}{a_k}\right)
\]

(5)

where $t = [t_1, t_2, \ldots, t_N] \in \mathbb{R}^N$ and $c_{kn}$ are the connection weight from the $n$th input to the $k$th wavelet neuron.

3.3. Wavelet network controller based on NARMA-L2 model

Combining the wavelet transform theory with the basic concept of NARMA-L2 model, a new mapping network called wavelet network (WN) is proposed. Figure 4, shows the structure of wavelet network NARMA-L2 (WN-NARMA-L2) representation for $d = 2, m = 3$ and $n = 2$. Notice that we have separate subnetworks to represent the functions $f[\bullet]$ and $g[\bullet]$. The blocks labeled TDL are tapped delay lines that store pervious values of the input and output signals.
4. Application to the UTSG water level control and simulation results

In this section we will use the model of section 2, to generate training data and simulate UTSG water level control. The block diagram of the control system is shown in figure 6. Like the conventional three-element SG level control system, the proposed control system is equipped with a feedforward scheme for steam flow. Therefore, $u$ in (2) is the difference between feedwater flow rate and steam flow rate ($Q_f - Q_s$), and $y$ is the water level.

We want to design a controller for power 5%. To this end, the first step is the development of the plant model in this power. The performance of designed wavelet network controller is highly dependent on the accuracy of plant identification. Here, we collect training data while applying inputs which consist of a series of ramps with different slopes. Two feedforward wavelet networks (figure 4) with six neurons in hidden layers are used to identify the UTSG model. The hidden neurons have Morlet activation functions while the output neurons are linear. For obtaining the plant input and output orders $n$ and $m$, we simply discretize the plant model with a zero order hold. The result is $n=3$ and $m=4$. We collect 2000 samples with sampling time 1 s. The network is trained off-line with these samples using a backpropagation algorithm, resulting to an MSE of about $10^{-12}$. Now this network is used the structure of figure 6.

Performance of the water level controller is evaluated by how well it tracks the setpoint and effectively it deals with the steam flow rate change. Figure 7, compares the performance of the proposed WN controller and the conventional PI controller at 5% power level. PI controller gains were
Figure 7. Comparison of the proposed controller and PI controller at 5% power level under the step change of the water level setpoint and the ramp and step changes of the steam flow rate. (a) water level and (b) feedwater flow rate.

optimized by a genetic algorithm (see [11]). The setpoint of the water level is increased from 0 mm to 100 mm at $t=500$ s. The steam flow rate is increased gradually between 1200 and 1400 s and then the step increase and decrease (17.22 kg/sec) in its magnitude occur at $t=2000$ s and $t=2500$ s, respectively. As shown in figure 7a, the undershoot in water level due to PI controller is -47 mm, while applying WN controller reduces it to approximately -20 mm. The settling time of water level response using WN controller is 480 s, whereas for PI controller, it is 700 s. Also, WN controller removes water level deviation (due to the sudden increase/decrease of steam flow rate) faster than PI controller. The control inputs, feedwater flow rate, generated by the WN and PI controllers are shown in figure 7b. When the water level setpoint increases at $t=500$ s, a narrow impulse of 78 kg/s appears in feedwater flow rate delivered by PI controller, which is unsuitable considering the limited rating of pumps. On the other hand, WN controller generates a slow and smooth change in feedwater flow rate. Altogether it can be said that the proposed controller causes less shrink and swell phenomena and offers faster settling time than the PI controller.

5. Conclusion

Control of UTSG water level strongly affects nuclear power plant availability. There has been a special interest in this problem during low power transients because of the dominant reverse thermal dynamic effects known as shrink and swell. In this work, a wavelet neural controller was developed to control the water level of nuclear steam generators at 5% nominal power. Comparisons between WN controller and a well-tuned PI controller show an improvement in water level setpoint tracking and an increased ability in disturbance (in the form of steam flow rate changes) rejection. As part of our future work, we will design a WN controller for all operating powers.

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