Annals of Nuclear Energy 69 (2014) 260–266

Contents lists available at ScienceDirect

Annals of Nuclear Energy

journal homepage: www.elsevier.com/locate/anucene

Power level control of the TRIGA Mark-II research reactor using the multifeedback layer neural network and the particle swarm optimization

Ramazan Coban *

Cukurova University, Department of Computer Engineering, 01330 Balcali, Saricam, Adana, Turkey

ARTICLE INFO

Article history:
Received 23 October 2013
Received in revised form 17 February 2014
Accepted 21 February 2014
Available online 14 March 2014

Keywords:
Intelligent control
Recurrent neural networks
Nuclear research reactor
Particle swarm optimization

ABSTRACT

In this paper, an artificial neural network controller is presented using the Multifeedback-Layer Neural Network (MFLNN), which is a recently proposed recurrent neural network, for neutronic power level control of a nuclear research reactor. Off-line learning of the MFLNN is accomplished by the Particle Swarm Optimization (PSO) algorithm. The MFLNN-PSO controller design is based on a nonlinear model of the TRIGA Mark-II research reactor. The learning and the test processes are implemented by means of a computer program at different power levels. The simulation results obtained reveal that the MFLNN-PSO controller has a remarkable performance on the neutronic power level control of the reactor for tracking the step reference power trajectories.

1. Introduction

Control of a nuclear reactor power level is challenging since the dynamic of the reactor is very complex, nonlinear, time-varying, also includes saturation, dead time, and changes with operating conditions. Although a reactor control problem can be solved manually by an expert human operator or automatically by a classical controller such as a PID-type, these control solutions suffer performance degradation, lack of safety, and take so much time to tune the parameters. To get a satisfactory performance and a safe control operation, the application of modern or expert control methods such as neural network control presents a powerful challenge.

In the last decade, a few authors have studied the application of the artificial neural network control in the nuclear reactor power level control. Arab-Alibeik and Setayeshi (2005) proposed a neural adaptive inverse controller to control the core power of a PWR reactor. After the emulation of the inverse dynamic of the reactor was obtained by the multilayer neural networks, it was used as a controller. However, it is always not possible to get inverse of the plants. Pérez-Cruz and Poznyak (2008) suggested a neural network controller for power ascent of a TRIGA research reactor. A single layer second order differential neural network accomplished the on-line identification. This identifier is used to achieve the indirect adaptive control action. In another paper, an indirect adaptive controller for nuclear research reactors based on a generalized Hopfield neural network was presented by Pérez-Cruz and Poznyak (2010). Pérez-Cruz et al. (2011) proposed constrained neural network control for the adaptive tracking of power profiles in the TRIGA Mark-III research reactor. For the TRIGA Mark-II nuclear research reactor in Turkey a trajectory tracking genetic fuzzy logic controller was designed by Coban and Can (2010). Recently, Coban (2011) suggested a fuzzy controller design for the TRIGA Mark-II nuclear research reactor using the Particle Swarm Optimization (PSO) algorithm. Liu and Cai (2012) have studied the fuel loading pattern optimization for a typical pressurized water reactor (PWR) using improved pivot PSO algorithm.

The particle swarm optimization algorithm among different computational optimization algorithms is preferred to train the controller parameters. In Dong et al. (2011), the PSO fuzzy neural network control is used for the ball and plate system. In that study, the PSO algorithm is used for the fuzzy neural network optimization. In Sheikhan et al. (2012), neural based controller is used for adaptive queue control in transmission control protocol communication. In the study, the PSO algorithm is exploited for training of the weights of the neural network based controller.

Generally speaking, Feedforward Neural Networks (FNNs) and Recurrent Neural Networks (RNNs) are used for control of dynamic systems. Since a feedforward neural network which realizes static mapping does not include dynamic memory, the tapped-delay-line (TDL) method is commonly used for efficiently control of dynamic systems. Nonetheless, this method has poor performance. Due to

* Tel.: +90 322 3387101x15; fax: +90 322 3386326.
E-mail address: rcoban@cu.edu.tr

http://dx.doi.org/10.1016/j.anucene.2014.02.019
0306-4549/

Nomenclature

MFLNN	multifeedback-layer neural network
PSO	particle swarm optimization
ITU	Istanbul Technical University
$n(t)$	neutron density
$\rho(t)$	total reactivity
β	total delayed neutron fraction
Λ	neutron generation time
λ_i	ith group delayed neutron decay constant
$C_i(t)$	ith group precursor concentration
β_i	ith group delayed neutron fraction
$T_f(t)$	fuel temperature
$P(t)$	reactor power
ρ_f	density of fuel
V_f	volume of the fuel
C_f	heat capacity of the fuel
N	number of the fuel elements
μ	total heat transfer coefficient of a fuel element
$T_m(t)$	coolant temperature
$\rho_m(t)$	density of coolant
V_m	volume of the coolant
C_m	heat capacity of the coolant
$\dot{m}_p(t)$	total mass flow rate of coolant
C	specific heat
$T_{\min}$	inlet temperature of coolant
$u(t)$	coolant velocity
u_{oi}	inlet coolant velocity
u_o	outlet coolant velocity
ζ	friction loss factor
ρ_{oi}	coolant inlet density
ρ_o	coolant exit density
g	gravity
H_c	total core height
$I(t)$	iodine concentration
γ_I	yield constant for Iodine
λ_I	decay constant for Iodine
Σ_f	thermal group macroscopic cross section
v_n	neutron velocity
$x(t)$	Xenon concentration
γ_x	yield constant for Xenon
λ_x	decay constant for Xenon
σ_x	thermal microscopic absorption cross section for Xenon
x_0	initial value of Xenon concentration
γ_f	energy released in a nuclear fission reaction
$\rho_{ex}(t)$	external reactivity inserted into reactor
$\alpha_f(T_f)$	temperature coefficient of reactivity
T_{f0}	initial temperature of a fuel
W_1	weight between the input and the hidden layer in the feedforward path
W_2	weight between the hidden and the output layer in the feedforward path
W_i^b	input weights of the feedback layer neurons
W_i^c	output weights of the feedback layers
$h^c(k)$	output of the hidden to hidden feedback layer neurons
$y^c(k)$	output of the output to hidden feedback layer neurons
$z^c(k)$	output of the feedback layer neurons
$\hat{y}(k)$	desired output
$y(k)$	actual output
B_i^b	bias values of the feedback layer neurons
$\varphi^c_{h,y,z}$	activation functions of the feedback layer neurons
$net_h(k)$	the local fields of the hidden layer neurons
φ_h	activation function of the hidden layer
$net_y(k)$	local field of output layer neurons
d	index of dimension of the search space (D)
i	index of the particle in the swarm (S_S)
r_i	random number which are uniform distribution in the range $[0, 1]$
c_i	positive coefficients
w	inertia weight
v_{id}	velocity of each particle
x_{id}	current position of each particle
gbest	best solution of the neighbors
pbest	best location of each particle
p_{id}	position of the *pbest*
p_{gd}	position of the *gbest*
k	iteration number
K	number of total iterations
P_0	initial steady-state power level
P_d	desired power
U	control action
e	error
f_e	fitness function related to tracking error (set point error)
$f_{OS\%}$	fitness function related to percent overshoot
N_T	size of data in a transient
$P_{\max}$	maximum or peak value of the reactor power at the peak time
Ψ	penalty coefficient for violation
$OS\%$	percent overshoot
e_{ss}	steady-state error
$t_{\max}$	duration of a transient

their intrinsic recurrence and dynamic mapping attribute, recurrent neural networks have superior performance, fast learning capability, and use less memory. Hence, recurrent neural network methods are important tools to realize linear or nonlinear controllers. Some kinds of recurrent neural networks are successfully applied to the nonlinear dynamic systems for control or identification purposes in Chow and Fang (1998), Coban (2013), Kim et al. (1997), and Savran (2007). The Multifeedback Layer Neural Network (MFLNN) proposed by Savran (2007) among them is one of the recurrent neural network methods and used to control the neutronic power level of the nuclear research reactor in this study because of its powerful ability to learn control laws. The MFLNN which is a very new version of the recurrent neural networks has three feedback layers for recurrence unlike the other RNNs which has simple feedback elements (Savran, 2007). For the MFLNN training, the PSO algorithm is selected here. The derivative based algorithms such as the back-propagation and Levenberg-Marquart (LM) algorithms necessitate desired values of the network's output or Jacobian of the system during the training in order to get error of the controlled system. Consequently, it is not suitable for controller design (Aksu, 2013). For this purpose, the PSO is preferred to train the MFLNN. For the first time in the literature, the controller based on the MFLNN-PSO is applied to the neutronic power level control of a nuclear research reactor. In the proposed MFLNN-PSO controller scheme a designer does not need the inverse dynamic of the plant unlike the other configurations presented in Arab-Alibeik and Setayeshi (2005), Pérez-Cruz et al. (2011), Pérez-Cruz and Poznyak (2008), and Pérez-Cruz and Poznyak (2010).

In this paper, a neural network controller is designed for control of the neutronic power level control of the nuclear research