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SYNTHESIS OF A NOVEL ROBUST INTELLIGENT CASCADED REACTIVITY CONTROLLER FOR CANDU REACTOR

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ABSTRACT

In this paper, a Novel Intelligent Cascaded Reactivity Controller (NICRC) is synthesized for a CANadian Deuterium Uranium (CANDU) -type Nuclear Power Plant (NPP) operating in Pakistan. The designed NICRC is a cascaded configuration of reactor power and moderator level controllers composed of five sub-controllers. The proposed NICRC is designed using intelligent soft computing technique. The original reactivity controller of CANDU nuclear power plant is a networked controller implemented on a Programmable Logic Controller (PLC). The new NICRC is designed based on two Intelligent Distributed Cascaded Power Controller (IDCPC) and Intelligent Cascaded Moderator Level Controller (ICMLC) for moderator level control in CANDU reactor core. The IDCPC is composed of three neural sub-controllers while ICMLC is composed of two neural sub-controllers. The proposed NICRC is designed using Adaptive Back Propagation Feedforward Neural Network (ABPFNN). The proposed controller is synthesized in a distributed parallel computing environment using MATLAB. The proposed NICRC is formulated in a highly complex multi-objective neural form and evaluated against full power operation of CANDU nuclear power plant from cold start-up to high power. The performance of highly robust NICRC is tested and evaluated for a typical transient providing complete coverage of moderator level, low log and steam pressure modes of CANDU reactor and found excellent within the desired control bands.

KEY WORDS: *Networked Control, Reactivity control, Cascaded Control, Distributed Control, Soft Computing, CANDU.*

INTRODUCTION

An operating CANDU-type nuclear power plant of 137 MWe rating is considered in this research work. CANDU Reactor power is controlled by different means. Amongst different means of power manipulation, the modulation of moderator level control valve is the most worthwhile. The modulation of this control valve is responsible for reactivity variation in the reactor core that in turns adjusts the reactor power. The existing reactivity controller is a networked controller implemented on distributed Programmable Logic Controllers (PLCs). All control logic changes are vendor supported[1] and therefore this reactivity control system is supposed to be a Black Box for this design engineering. Hence, it is required to identify this black box controller through thorough investigations of existing networked reactivity controller so as to design a novel controller mimicking the existing controls.

A spatial decentralized periodic output feedback controller for 540 MWe PHWR has been designed in[2] using liquid zone control concept. A discrete higher order nonlinear spatial sliding mode controller has been suggested for the same Indian 540 MWe PHWR in[3]. A model predictive power controller and robust power controller for the same CANDU-type PHWR[1] have been proposed in[4,5] using CARIMA predictive control design and H_∞ robust control design algorithms respectively. A PID controller has been designed and tuned using artificial neural network for PWR pressurizer water level controller in[6]. A Distributed Control System (DCS) based core monitoring system for 600 MWe CANDU has been designed in[7] for flux and channel powers using programmable logic controllers configured in distributed configuration. A Controller Area Network (CAN) based networked controller has been suggested in[8] for a power plant and design issues related to CAN have been presented for power plant applications. A DCS based instrumentation and control has been reviewed in detail for nuclear, primary and secondary loops for nuclear power plant in[9]. A networked controller has been designed for PWR pressurizer light water level

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controller in[10] that compensates the reactor coolant pressure dynamics which is associated with water and steam ratio in pressurizer. A network fuzzy PID controller has been proposed for power plant steam temperature control in[11] addressing the process, network and system delays. A fuzzy logic based intelligent DCS control system has been designed for fossil power plant in[12] using Mamdani type inference engine in MATLAB environment. A neural network tuned PID controller has been designed for networked multivariable cascaded chemical processes in[13].

In this research work, a novel design approach has been adopted for replacing networked reactivity controller using intelligent cascaded Multi-Input Multi-Output (MIMO) and Multi-Input Single-Output (MISO) sub-controllers due to coupled internal dynamics of inputs and outputs of conventional controller parameters without loss of parametric information and to minimize Mean Square Error (MSE) with fast convergence for both moderator valve position and reactor power in distributed parallel configuration with robust performance for a CANDU-type nuclear power plant. One Intelligent Distributed Cascaded Power Controller (IDCPC) has been designed using one MIMO and two MISO sub-controllers. The MIMO sub-controller has been designed to control steam pressure offset compensation, stream pressure rate compensation, steam pressure compensation, reactor power demand, power correction factor and turbine demand while the two MISO sub-controllers have been designed to control computed reactor power set-point and compensated reactor power respectively. Second Intelligent Cascaded Moderator Level Controller (ICMLC) has been designed using one MIMO and one MISO sub-controllers. The MIMO sub-controller has been designed to control moderator level compensation, logarithmic power compensation, rate logarithmic power compensation, power mismatch compensation, low log compensation, valve bias and total control demand while the MISO sub-controller has been designed to control moderator valve position. A neural network network based control design strategy has been adopted because a three layer ANN architecture is relatively easy and simple in complexity for multivariable intelligent controller design as compared to fuzzy logic based intelligent controller design.

DISTRIBUTED NETWORKED REACTIVITY CONTROLLER

The reactivity controller of CANDU-type nuclear power plant is implemented on a DCS. The DCS is basically a networked control system. It uses plant Local Area Network (LAN) and a very specialized PLC based controller called AC-132-16 controller. It is a proven technology adopted from a Belgium nuclear power plant[1]. This controller is modular in nature and has a wide library of analog and digital control modules but has limited modification and data trending facility. All process parameters are acquired from the plant via process sensors while neutronic parameters via ion chambers or nuclear detectors. Since the reactivity controller has multiple set-points and multiple feedback signals and therefore it is called a multivariable controller. The implementation of reactivity controller on DCS is a huge physical setup and is presented in a simplified block diagram form as shown in Figure 1.

Nuclear instrumentation system is used for linear reactor power, logarithmic reactor power and rate of change of logarithmic reactor power measurements while plant temperature monitoring system is used for core inlet header temperature, core outlet temperature and primary coolant flow. Plant load controller is a MWe demand setter which has corresponding value in % RP (Reactor Power). This controller is interfaced with networked reactor power controller. The plant sensors, AC-132-16 controller, converters and actuators forms a CANDU process sensored network for a reactor power regulating system as shown in Figure 1. The reactor power regulating system is basically a fine and very slowly progressing power control system based on reactivity perturbation in reactor core. All the necessary parameters are shown in Figure 1. All process and controller parameters are not static in nature and therefore parameters have dynamic values under plant different conditions. The parametric variations are discussed in detail in both tabular and graphical forms.

INTERACTION OF REACTIVITY CONTROLLER WITH CONTROL AND MONITORING LOOPS

The networked reactivity controller is coupled with various other control and monitoring loops as shown in Figure 2.

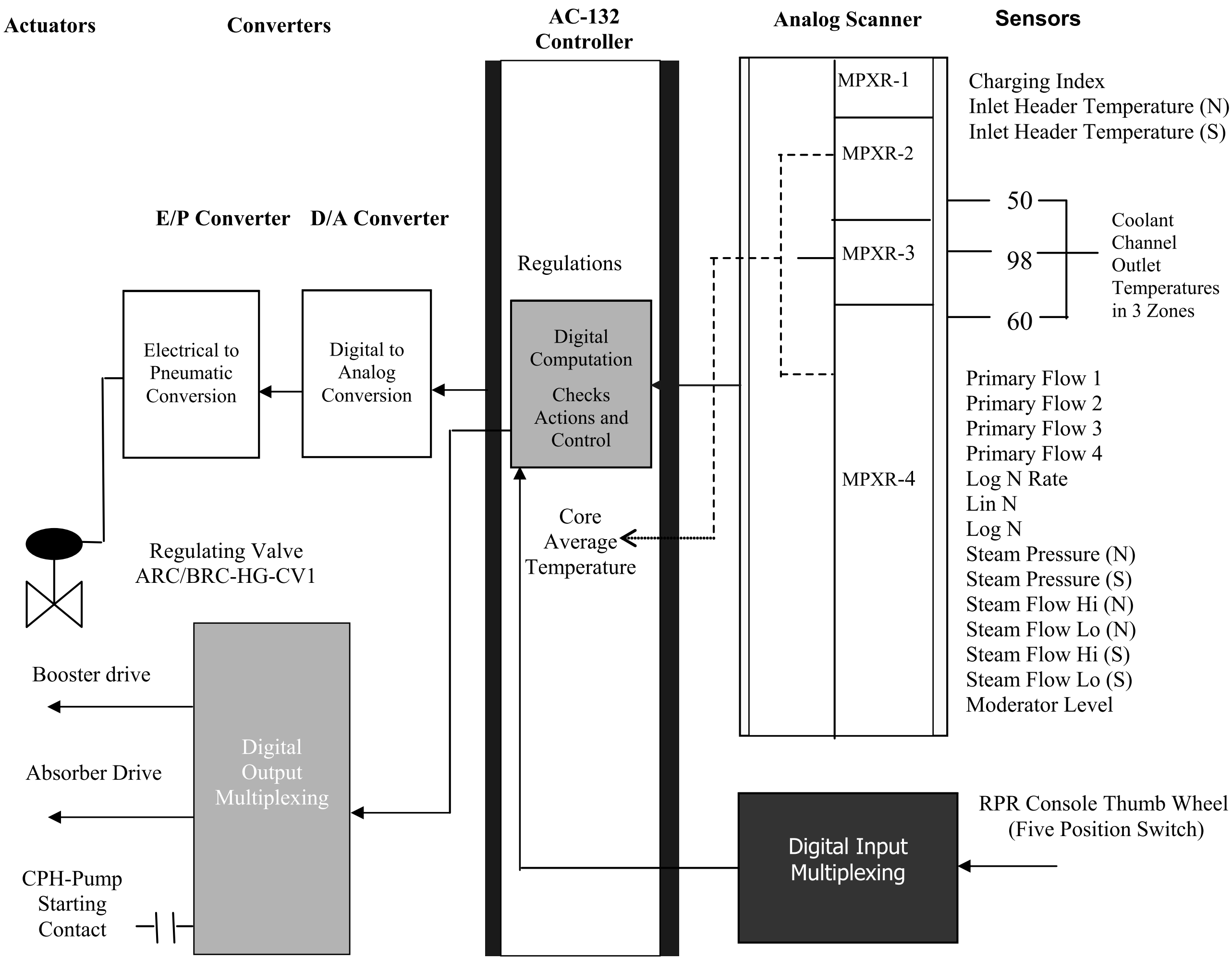

Figure 1: Candu Process Sensored Network For Reactor Regulating System

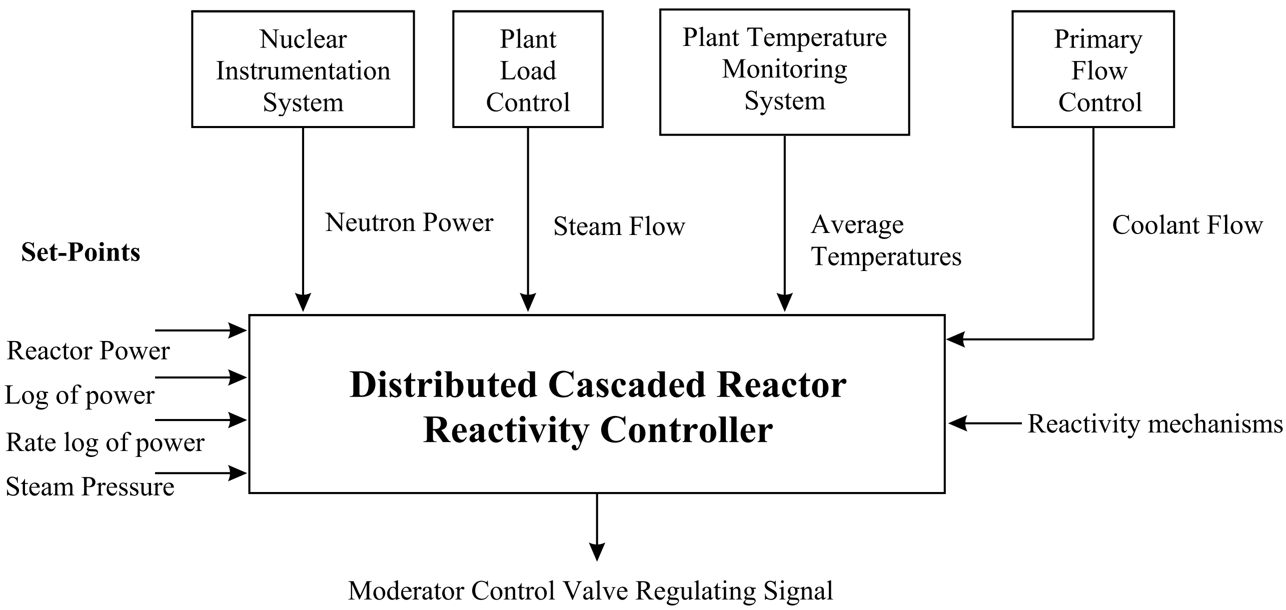

Figure 2: Integration of Different Control Loops with Intelligent Reactivity Controller for a nuclear power plant

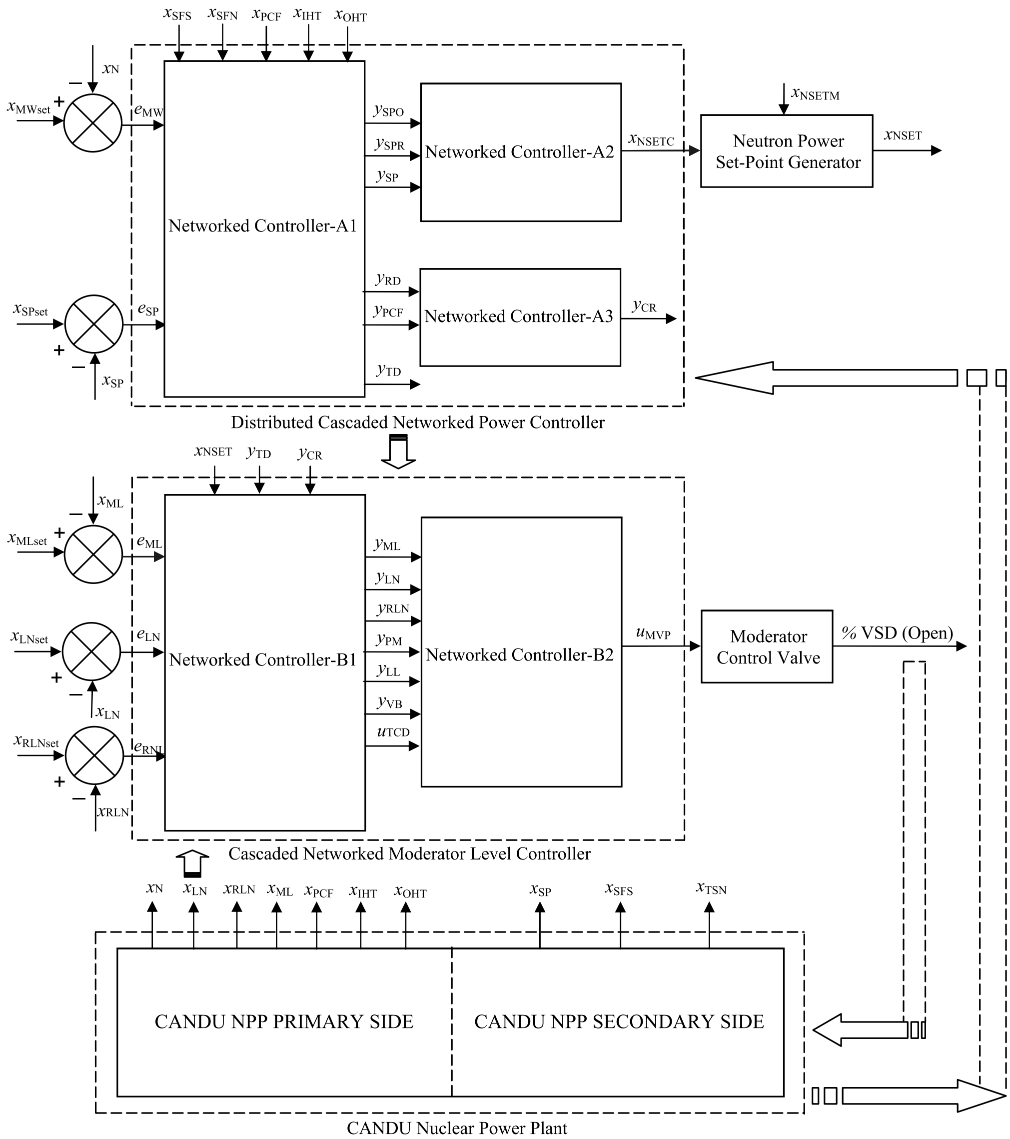

Figure 3: Design configuration cascaded moderator level and distributed cascaded power controller for nuclear power plant

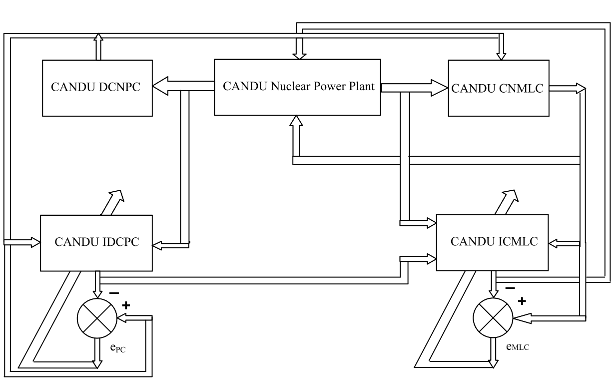

Figure 4: Design Configuration of New Intelligent Cascaded Reactivity Controller for Nuclear Power Plant

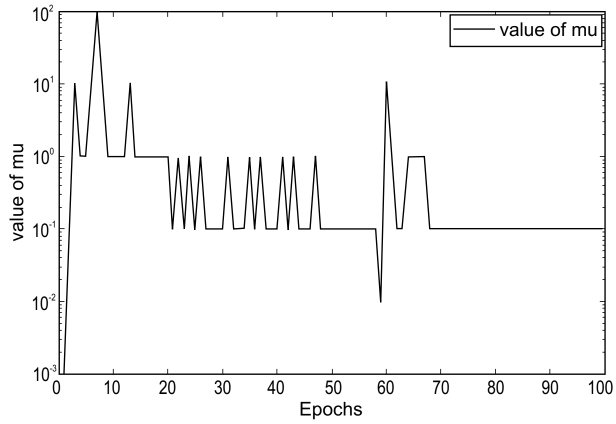

Figure 5: Variation of MU with Epochs for Moderator Level Controller

The CANDU networked reactivity controller is interfaced with following control and monitoring loops:

1) Plant temperature monitoring system

2) Nuclear instrumentation system

3) Primary flow control system

4) Plant load control system

DESIGN ANALYSIS OF CASCADED NETWORKED REACTIVITY CONTROLLER

The reactor power of CANDU reactor is controlled mainly by means of reactivity controller which is responsible for moderator level rise or fall in the reactor core although there reactor power can also be controlled by rod controller and chemical shim controller. But new controller is designed for a scenario in which chemical shim and rod controllers are inactive. Therefore, in this scenario, the reactivity controller is basically a cascaded controller consisting of reactor power controller and moderator level controller. The reactor power controller is a distributed cascaded networked controller which is composed of three sub-controllers A1, A2 and A3. The inputs and outputs of reactor power controller are tabulated in Tables 1 and 2 respectively. The moderator level controller is a cascaded networked controller which is composed of two sub-controllers B1 and B2. The inputs and outputs of moderator level controller are tabulated in Tables 3 and 4 respectively. After thorough investigations, a detailed design of cascaded networked reactivity controller is developed which is shown in Figure 3.

SYNTHESIS OF NEW INTELLIGENT CASCADED REACTIVITY CONTROLLER

An intelligent system is one that mimics a physical system treating it as black box and maps its dynamics in nonlinear form while a cascaded system consists of two or more sub-systems and is configured in such a way that the output of first sub-system acts likes an input for second sub-system and so forth. A cascaded system helps in capturing the detailed internal dynamics of a complex large scale system for parametric analysis and design[12].

In this research work, a new intelligent cascaded reactivity controller has been proposed for an operating CANDU-type nuclear power plant. The proposed controller is designed using data driven approach in a closed loop configuration.

Neural Network Based Reactivity Controller

As the original networked reactivity controller is a multivariable controller, therefore, an artificial intelligence based controller is the best choice for control synthesis. The new reactivity controller mimics the same control structure in neural environment.

Internal Dynamics of Neural Sub-Controllers

Each neural sub-controller of intelligent distributed cascaded power controller (IDCPC) and intelligent cascaded moderator level controller (ICMLC) has three layer topology.

The basic design of each neural sub-controller has an adaptive feed forward architecture. Each neural sub- controller is designed using standard Back Propagation Algorithm (BPA) optimized by Gradient Decent Learning Rule (GDLR)[13].

The level of complexity of each neural sub-controller depends on the selection of neurons in hidden layer. Each neural sub-controller is of sufficiently high dimension.

Intelligent Distributed Cascaded Power Controller

The intelligent distributed cascaded controller consists of three neural sub-controllers. Neural sub-controllers A1N and A2N form first cascaded configuration while neural sub-controllers A1N and A3N form second cascaded configuration. Both these cascaded configurations form intelligent distributed cascaded configuration of reactor power controller as shown in Figure 3.

Intelligent Cascaded Moderator Level Controller

The intelligent cascaded moderator level controller consists of two neural sub-controllers. Neural sub-controllers B1N and B2N form a cascaded configuration as shown in Figure 3.

Selection of Shaping Function for Neural Sub-Controllers

Since the dynamics of each sub-controller is highly nonlinear, therefore, a sigmoid type shaping function is chosen for each neural sub-controller synthesis as it is best suited for highly nonlinear dynamical systems[6]. The sigmoid type shaping function is a nonlinear function and can be mathematically represented as:

$$f(x) = \frac{1}{1 + e^{-mu\,x}} \qquad (1)$$

where *mu* is called the shaping parameter.

Synthesis of Performance Indices for Reactor Power Controller

Since, the intelligent distributed cascaded power controller is a combination of multiple neural sub-controllers, so a separate performance index has to be defined for each neural sub-controller.

If u_{A1} is an input vector for neural sub-controller- A1N, y_{A1} is an output vector for sub-controller- A1 and y_{A1N} is an output vector for neural sub-controller- A1N then input vector and output vector of sub-controller- A1and output vector of MIMO neural sub-controller- A1N can be formulated as:

$$u_{A1}(k) = \left[e_{MW}(k), e_{SP}(k), x_{SFN}(k), x_{SFS}(k), x_{PCF}(k), x_{IHT}(k), x_{OHT}(k)\right]^{T}$$

$$y_{A1}(k) = \left[y_{SPO}(k), y_{SPR}(k), y_{SP}(k), y_{RD}(k), y_{PCF}(k), y_{TD}(k)\right]^{T}$$

$$y_{A1N}(k) = \left[y_{SPON}(k), y_{SPRN}(k), y_{SPN}(k), y_{RDN}(k), y_{PCFN}(k), y_{TDN}(k)\right]^{T}$$

Now, the objective is to formulate the problem for the optimization of a neural sub-controller-A1N. The performance index of a MIMO neural sub-controller-A1N in terms of mean square error can be formulated as:

$$J_{A1N}(k) = \frac{1}{2}\sum_{k=1}^{n}[y_{A1N}(k) - y_{A1}(k)]^2 = \frac{1}{2}\sum_{k=1}^{n}[e_{A1}(k)]^2 \qquad (2)$$

Similarly, if u_{A2N} is a neural input vector for neural sub-controller- A2N, y_{A2} is an output for sub-controller- A2 and y_{A2N} is an output for neural sub-controller-A2N then input vector and output for sub-controller-A2 and output for neural sub-controller- A2N can be formulated as:

$$u_{A2N}(k) = \left[y_{SPON}(k), y_{SPRN}(k), y_{SPN}(k)\right]^{T}$$

$$y_{A2}(k) = \left[y_{NNSETC}(k)\right]$$

$$y_{A2N}(k) = \left[y_{NNSETCN}(k)\right]$$

Now, the objective is to formulate the problem for the optimization of a neural sub-controller-A2N. The performance index of a MISO neural sub-controller-A2N in terms of mean square error can be formulated as:

$$J_{A2N}(k) = \frac{1}{2}\sum_{k=1}^{n}[y_{A2N}(k) - y_{A2}(k)]^2 = \frac{1}{2}\sum_{k=1}^{n}[e_{A2}(k)]^2 \qquad (3)$$

Similarly, if u_{A3N} is a neural input vector for neural sub-controller- A3N, y_{A3} is an output for sub-controller- A3 and y_{A3N} is output for neural sub-controller- A3N then input vector and output for sub-controller- A3 and output for neural sub-controller-A3N can be formulated as:

$$u_{A3N}(k) = \left[y_{RDN}(k), y_{PCFN}(k)\right]^{T}$$

$$y_{A3}(k) = \left[y_{CR}(k)\right]$$

$$y_{A3N}(k) = \left[y_{CRN}(k)\right]$$

Now, the objective is to formulate the problem for the optimization of a neural sub-controller-A3N. The performance index of a MISO neural sub-controller-A3N in terms of mean square error can be formulated as:

$$J_{A3N}(k) = \frac{1}{2}\sum_{k=1}^{n}[y_{A3N}(k) - y_{A3}(k)]^2 = \frac{1}{2}\sum_{k=1}^{n}[e_{A3}(k)]^2 \qquad (4)$$

Synthesis of Performance Indices for Moderator Level Controller

Since, the intelligent cascaded moderator level controller is combination of multiple neural sub-controllers, so a separate performance index has to be defined for each neural sub-controller.

If u_{B1M} is a mixed input vector for neural sub-controller- B1N, y_{B1} is an output vector for sub-controller- B1and y_{B1N} is an output vector for neural sub-controller- B1N then input vector and output vector for sub-controller- B1and output vector for MIMO neural sub-controller- B1N can be formulated as:

$$u_{B1M}(k) = \left[e_{ML}(k), e_{LN}(k), x_{RLN}(k), x_{NSETN}(k), y_{TDN}(k), y_{CRN}(k)\right]^{T}$$

$$y_{B1}(k) = \left[y_{ML}(k), y_{LN}(k), y_{RLN}(k), y_{PM}(k), y_{LL}(k), y_{VB}(k), u_{TCD}(k)\right]^{T}$$

$$y_{B1N}(k) = \left[y_{MLN}(k), y_{LNN}(k), y_{RLNN}(k), y_{PMN}(k), y_{LLN}(k), y_{VBN}(k), u_{TCDN}(k)\right]^{T}$$

Now, the objective is to formulate the problem for the optimization of a neural sub-controller-B1N. The performance index of a MIMO neural sub-controller-B1N in terms of mean square error can be formulated as:

$$J_{B1N}(k) = \frac{1}{2}\sum_{k=1}^{n}[y_{B1N}(k) - y_{B1}(k)]^2 = \frac{1}{2}\sum_{k=1}^{n}[e_{B1}(k)]^2 \qquad (5)$$

Similarly, if u_{B2N} is a neural input vector for neural sub-controller- B2N, y_{A2} is an output for sub-controller- B2 and y_{B2N} is an output for neural sub-controller- B2N then input vector and output for sub-controller- B2N and output for neural sub-controller-B2N can be formulated as:

$$u_{B2}(k)=[y_{MLN}(k), y_{LNN}(k), y_{RLNN}(k), y_{PMN}(k), y_{LLN}(k), y_{VBN}(k), u_{TCDN}(k)]^T$$

$$y_{B2}(k)=[u_{MVP}(k)]$$

$$y_{B2N}(k)=[u_{MVPN}(k)]$$

Now, the objective is to formulate the problem for the optimization of a neural sub-controller-B2N. The performance index of a MISO neural sub-controller-B2N in terms of mean square error can be formulated as:

$$J_{B2N}(k)=\frac{1}{2}\sum_{k=1}^{n}[y_{B2N}(k)-y_{B2}(k)]^2=\frac{1}{2}\sum_{k=1}^{n}[e_{B2}(k)]^2 \quad (6)$$

RESULTS AND DISCUSSION

Now, in this section, the proposed design philosophy is evaluated for a CANDU-type nuclear power plant.

The design of proposed intelligent distributed cascaded reactivity controller is a plant model-free controller. Therefore, its training, testing and validation phases are carried out in a closed loop environment. The closed loop framework of a proposed controller is shown in Figure 4. The optimum neurons in the hidden layer are selected through an optimization program developed in MATLAB for both IDCPC and ICMLC. The process of optimization is carried out in which number of neurons are increased gradually and MSE is checked against each simulation experiment and hence based on minimum MSE, the optimum number of neurons are picked for both IDCPC and ICMLC and are found 40 and 20 neurons respectively. The variation of shaping factor *mu* for moderator level controller is shown in Figure 5. If *p* is the number of neurons in input layer (i.e. input nodes), *q* is the number of neurons in the hidden layer (i.e. hidden layer nodes) and *r* is the number of neurons in output layer (i.e. output nodes) then a neural network design topology can be expressed as *p*-*q*-*r*. Therefore, the design topologies of each neural sub-controller for IDCPC and ICMLC are shown in Tables 5 and 6 respectively. Total 8613 patterns of inputs and output of ICMLC are acquired from an operating CANDU-type nuclear power plant in Pakistan. These 8613 patterns are divided into three sets of data known as training, testing and validation datasets respectively. Training dataset contains 60% patterns (5169 samples), testing dataset contains 20% patterns (1722 samples) and validation dataset contains 20% patterns (1722 samples). Similarly, total 2782 patterns of inputs and output of IDCPC are acquired. These 2782 patterns are divided into three sets of data known as training, testing and validation datasets respectively. Training dataset contains 60% patterns (1670 samples), testing dataset contains 20% patterns (556 samples) and validation dataset contains 20% patterns (556 samples). Therefore, all the design parameters of both IDCPC and ICMLC are tabulated in Tables 7 and 8 respectively.

In IDCPC, as the design topology for neural sub-controller-A1N is 7-40-6 which is quite obvious from Figure 3. Therefore, the dimensions of hidden and output weight matrices and bias matrices of neural sub-controller-A1N are 40×7, 40×6, 6×40 and 6×6 order matrices respectively. Similarly, as the design topology for neural sub-controller-A2N is 3-40-1 which is quite obvious from Figure 3. So, the dimensions of hidden and output weight matrices and bias vectors of neural sub-controller-A2N are 40×3 order matrix, 40×1 order vector, 1×40 order vector and 1×1 single element respectively. In a similar way, as the design topology for neural sub-controller-A3N is 2-40-1 which is quite obvious from Figure 3. So, the dimensions of hidden and output weight matrices and bias vectors of neural sub-controller-A3N are 40×2 order matrix, 40×1 order vector, 1×40 order vector and 1×1 single element respectively.

In ICMLC, as the design topology for neural sub-controller-B1N is 5-20-7 which is quite obvious from Figure 3. Therefore, the dimensions of hidden and output weight matrices and bias vectors of neural sub-controller-B1N are 20×5 order matix, 20×7, 7×20 and 7×7 order matrices respectively. Similarly, as the design topology for neural sub-controller-B2N is 7-20-1 which is quite obvious from Figure 3. So, the dimensions of hidden and output weight matrices and bias vectors of neural sub-controller-B2N are 20×7 order matrix, 20×1 order vector, 1×20 order vector and 1×1 single element respectively.

Since in low power mode, the variations of moderator level controller parameters are visible while

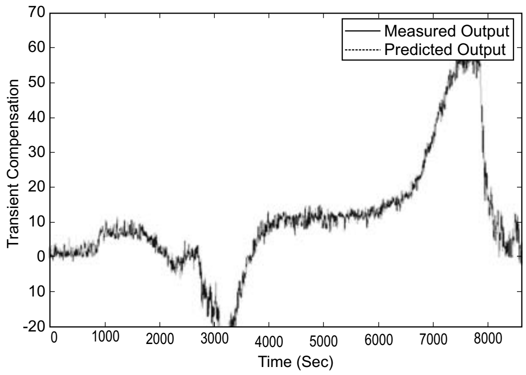

Figure 6: Comparison of measured and predicted transient compensation

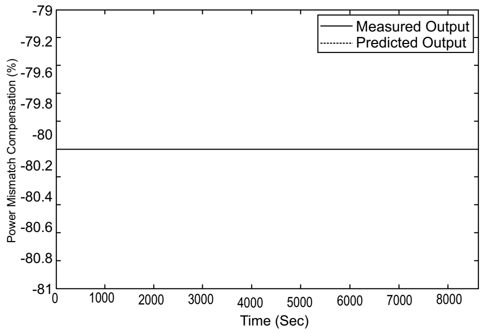

Figure 7: Comparison of measured and predicted power mismatch compensation

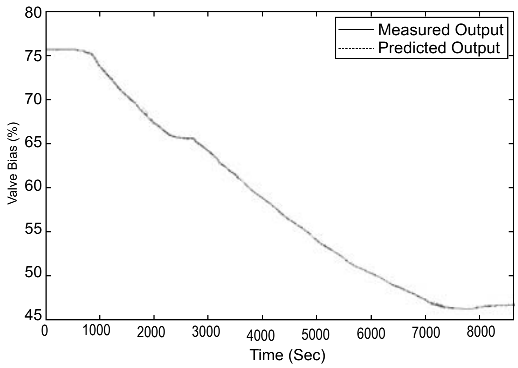

Figure 8: Comparison of measured and predicted valve bias compensation

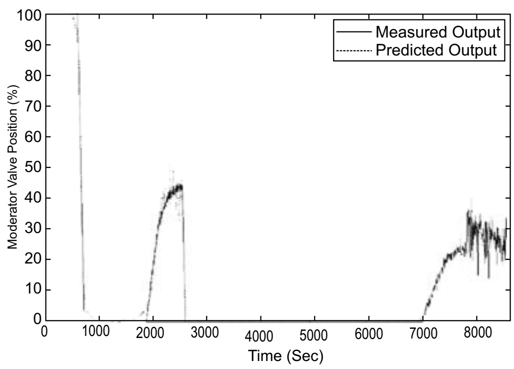

Figure 9: Comparison of measured and predicted moderator valve position

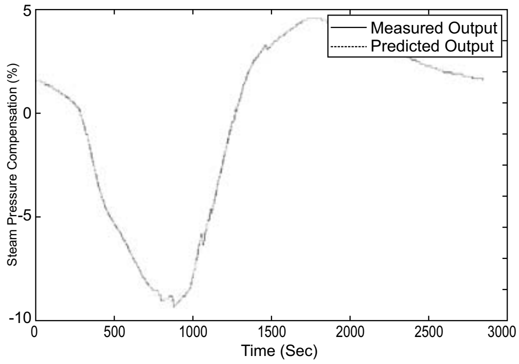

Figure 10: Comparison of measured and predicted steam pressure off-set compensation

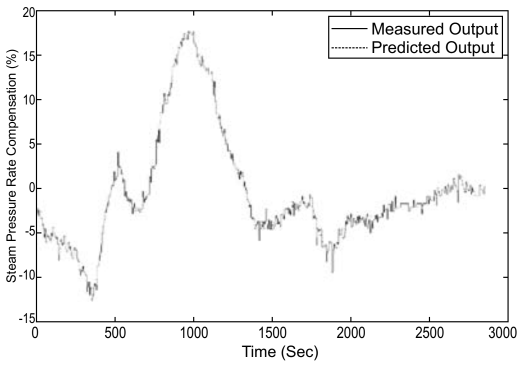

Figure 11: Comparison of measured and predicted steam pressure rate compensation

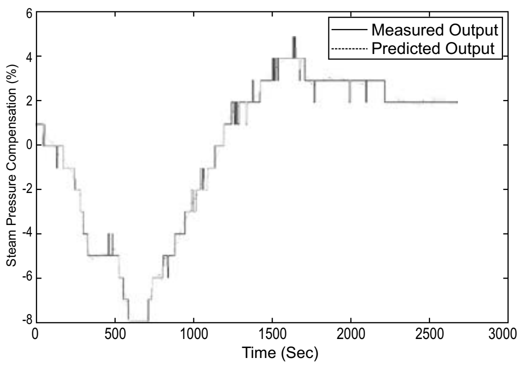

Figure 12: Comparison of measured and predicted steam pressure compensation

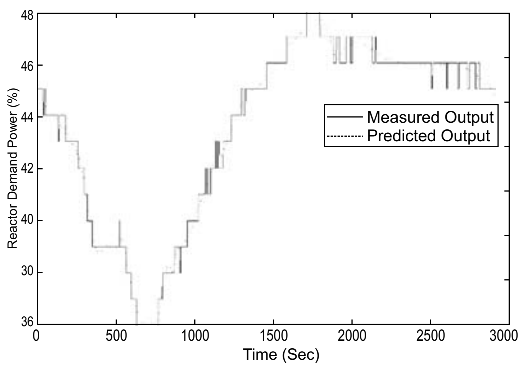

Figure 13: Comparison of measured and predicted reactor demand power

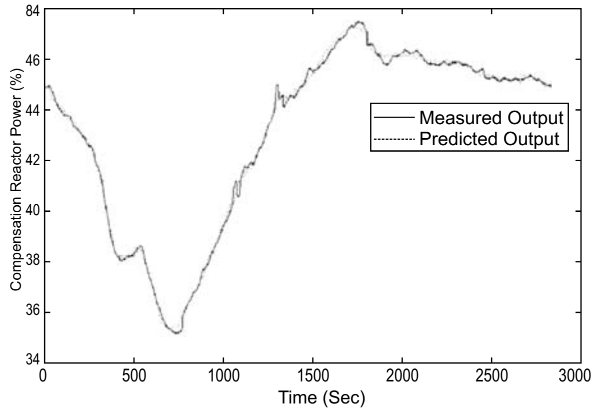

Figure 14: Comparison of measured and predicted compensated reactor power

Table 1: Input paramters of intelligent cascaded power controller

Parameters	Definitions
$x_{MWset}(k)$	MWe Set-Point (%)
$x_{N}(k)$	Linear Reactor Power (%)
$x_{SPset}(k)$	Steam Pressure Set-Point (Psig)
$x_{SP}(k)$	Steam Pressure (Psig)
$x_{SFN}(k)$	Steam Flow North (%)
$x_{SFS}(k)$	Steam Flow South (%)
$x_{IHT}(k)$	Inlet Header Temperature (°F)
$x_{OHT}(k)$	Outlet Header Temperature (°F)
$x_{PCF}(k)$	Primary Coolant Flow (lb/hr)

Table 2: Output paramters of intelligent cascaded power controller

Parameters	Definitions
$y_{SPO}(k)$	Steam Pressure Off-Set Compensation (%)
$y_{SPR}(k)$	Steam Pressure Rate Compensation (%)
$y_{SP}(k)$	Steam Pressure Compensation (%)
$P_{TD}(k)$	Turbine Demand Power (%)
$P_{RD}(k)$	Reactor Demand Power (%)
$y_{PCF}(k)$	Power Correction Factor
$P_{CR}(k)$	Compensated Reactor Power (%)
$x_{NSETC}(k)$	Computed Reactor Power Set-point (%) in SP Mode
$x_{NSETM}(k)$	Manual Reactor Power Set-point (%)

reactor power controller parameters are not visible because reactor power is too low while approaching to reactor criticality. Whereas in high power mode, the variations of moderator level controller parameters are not visible while reactor power controller

Table 3: Input paramters of intelligent cascaded moderator level controller

Parameters	Definitions
$x_{MLset}(k)$	Moderator Level Set-Point (inches)
$x_{ML}(k)$	Moderator Level (inches)
$x_{Nset}(k)$	Linear Reactor Power Set-Point (%)
$x_{N}(k)$	Linear Reactor Power (%)
$x_{LNset}(k)$	Log Reactor Power Set-Point (decades)
$x_{LN}(k)$	Log Reactor Power (decades)
$x_{RLNset}(k)$	Rate Log Reactor Power Set-Point (%/sec)
$x_{RLN}(k)$	Rate Log Reactor Power (%/sec)
$P_{TD}(k)$	Turbine Demand Power (%)
$P_{CR}(k)$	Compensated Reactor Power (%)

Table 4: Outputs paramters of intelligent cascaded moderator level controller

Parameters	Definitions
$y_{ML}(k)$	Moderator Level Compensation (%)
$y_{LN}(k)$	Log N Compensation (%)
$y_{RLN}(k)$	Transient Compensation (%)
$y_{PM}(k)$	Power Mismatch Compensation (%)
$y_{LL}(k)$	Lead-Lag Compensation (%)
$y_{VB}(k)$	Valve Bias (%)
$u_{TCD}(k)$	Total Control Demand (%)
$u_{MVP}(k)$	Moderator Valve Position (%)
%VSD (k)	% Valve Stoke Demand (% Open)

Table 5: Design topology of intelligent cascaded power controller

Neural Sub-Controller	Topology
Neural Sub-Controller-A1N	7-40-6
Neural Sub-Controller-A2N	3-40-1
Neural Sub-Controller-A3N	2-40-1

Table 6: Design topology of intelligent cascaded moderator level controller

Neural Sub-Controller	Topology
Neural Sub-Controller-B1N	6-20-7
Neural Sub-Controller-B2N	7-20-1

parameters are visible because in high power mode, reactor power controller parameters become independent of moderator level. Thus, the cascading of both controllers results in coverage of all parameters of reactivity controller. Therefore, patterns or discrete

Table 7: Design parameters of intelligent cascaded moderator level controller in low power mode

Design Parameters	Values
Total Number of Patterns (100%)	8613
Number of Training Patterns (60%)	5169
Number of Testing Patterns (20%)	1722
Number of Validation Patterns (20%)	1722
Number of Each Network Layers	3
Optimum Number of Neurons in Hidden Layer	40
Target MSE	0
Achieved Performance (MSE)	0.0019953786
Linear Regression	0.97874
Initial Shaping Factor (mu)	0.001
Target Epochs	100

Table 8: Design parameters of intelligent distributed cascaded power controller in high power mode

Design Parameters	Values
Total Number of Patterns (100%)	2782
Number of Training Patterns (60%)	1670
Number of Testing Patterns (20%)	556
Number of Validation Patterns (20%)	556
Number of Each Network Layers	3
Optimum Number of Neurons in Hidden Layer	20
Target MSE	0
Achieved Performance (MSE)	0.001801
Linear Regression	0.9996
Initial Shaping Factor (mu)	0.001
Target Epochs	100

samples are different for IDCPC and ICMLC. All pattern information and their sub classification for both IDCPC and ICMLC are clearly described in Tables 7 and 8 respectively.

The proposed cascaded reactivity controller is implemented for an operating CANDU nuclear power plant in Pakistan[1]. Since input and output parameters for IDCPC and ICMLC are large, therefore, some important parameters of interest are selected for analysis purposes. The variation of transient compensation, power mismatch compensation, valve bias and moderator valve position of ICMLC are shown in Figures (6)-(9). In Figure 6, the variation of transient compensation expressed in percentage is shown. The parameter transient compensation covers internally the impact of linear power, logarithmic power, rate logarithmic power and moderator valve bias. Since in this research work, a reactor power transient case has been presented in which initially the power is decreased from steady power level of 45% and then it is allowed to stabilize at 45% again. Therefore, the transient compensation parameter hunts around 0% value. So, initially this parameter initially has highly fluctuating negative value and then after 3500 seconds it has fluctuating positive value and ultimately settles down to zero when power transient stabilizes. In Figure 7, power mismatch compensation in percentage is shown. Power mismatch covers the compensation of turbine and reactor power and it should have -80% stable values throughout the transient. This value is set by the vender as reported in[1]. In Figure 8, a parameter value bias in percentage is shown. This parameter is provided to cover controller bias value in case proportional moderator valve demand failure. Therefore, it is a compensation parameter and it drifts as the moderator valve demand position changes. In Figure 9, the moderator valve position starts from 100% and during the transient it dynamically changes and ultimately settles down to 25% final value. The parametric variation of this moderator valve position depends on several other parameters as shown in Figure 3. All trends show excellent tracking of controller parameters. The variations of steam pressure off-set compensation, steam pressure rate compensation, steam pressure compensation and reactor demand power and compensated reactor of IDCPC are shown in Figures (10)-(14). In Figure 10, steam pressure off-set compensation in percentage is shown. This parameter covers the error fluctuation between steam pressure set-point (i.e. 550 psig) and measured steam pressure in psig when proportional and integral modes fluctuates during transient operation of nuclear power plant in high power mode. Therefore, finally, it should reach the same value from where it was initialed. In Figure 11, stream pressure rate compensation is expressed in percentage. It covers the derivate part of steam pressure fluctuations. Therefore, it is highly fluctuating in nature and hence stabilizes at 0%. In Figure 12, steam pressure compensation is shown in percentage. It deals with successive steam pressure fluctuations. Therefore, it initially it fluctuates in staircase manner and ultimately settles down at constant value of 2% as reported in[1]. In Figure 13, reactor demand power is shown in percentage. A reactor power transient has been introduced from a

δ ´

steady value of 45% and ended at the same value of 45%. It has staircase type response due to successive steam pressure fluctuations. In Figure 14, steam compensated reactor power is shown in percentage. This parameter smoothens out the staircase type power trend into a finely varying reactor power. All trends show excellent tracking of controller parameters. Amongst all parameters tracking, the prediction of steam pressure compensation and reactor demand power are found with much better performance in terms of smoothness, robustness, nonlinearity and overshoots reduction. Hence, an extremely successful realization has been observed against validation experiments through simulation trials when practically implemented on CANDU type operating nuclear power plant in Pakistan.

5. CONCLUSIONS

In this research work, an effort has been made to replace the networked reactivity controller of CANDU-type nuclear power plant by an intelligent controller operating in distributed cascaded mode. A thorough investigation has been made to identify the inputs and outputs of reactivity controller using moderating control valve as main modulating signal. The proposed controller has a neural architecture. The proposed intelligent controller is designed using distributed programming approach. The proposed controller has five neural sub-controllers optimized using standard Back Propagation Algorithm. The proposed controller is designed, tested and evaluated using ANN tool of MATLAB against a specially designed transient covering sub-critically, criticality and power operation of an operating CANU nuclear power plant.

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