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DEVELOPMENT OF DEEP LEARNING AND MODEL PRODUCTIVE CONTROL TO ENHANCE AUTOMATIC GENERATION CONTROL (AGC) IN INTERCONNECTED POWER SYSTEMS

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ABSTRACT

Every Country needs efficient, effective and balanced power system for the smooth running of its economy. To maintain power balance in the system, generation and load need to balance in order to uphold system frequency at the nominal value. Oscillation in the power system resulting from AGC problems could cause serious damages to generation and transmission assets on the power system. Cascaded collapse of the system from AGC problem could lead to a wide scale blackout. Such wide scale blackouts would impact on the country's Gross Domestic Product (GDP) as it is well known that electric energy usage impacts on and is a reflection of a country's GDP. Control is the key component in this regard. This is where Automatic Generation Control (AGC) comes into play. Automatic Generation Control in an electric power system, is the control system for regulating the power output of many generators at different power plants, in response to changes in the load. The balance can be determined by measuring the system frequency. The key objective of this work is development of deep Learning model predictive control MPC to enhance Automatic Generation Control (AGC) in interconnected power system and regulating tie-line power exchange for enhanced power balance in the controlled areas. To overcome the above limitations, this study proposes the use of software to enhance the effectiveness of RNN-MPC model in AGC operations.

KEYWORDS: Deep Learning, Model Predictive Control, Automatic Generation Control, Tie-Line and Frequency.

INTRODUCTION

In this work, the machine learning technique (deep learning (DL)) is integrated with model predictive control (MPC) for the generation of control signals for the control of the generator governors in the interconnected power system. The PI controller as used in most AGC system is essentially a fixed controller. This has implications for the development of a robust AGC system. The power system contains different kinds of uncertainties due to changes in system parameters and characteristics, load variations and errors in modeling. The operating points of the power system may change very much randomly during a daily cycle. Hence a fixed controller, such as PI/PID controller, that is based on conventional control theory is certainly not suitable for developing robust AGC systems.

In the design of the proposed AGC system, the flexible and adaptive control architecture model predictive controller is coupled with the industry leading machine learning method of deep learning in order to produce a robust self-tuning AGC system for interconnected power system. The control strategy developed here is essentially data-driven paradigm, that is, an integration of state –of-the-art machine learning and control algorithms to produce an enhanced easy to implement, learning module for robust AGC system.

MPC provides a robust architecture for explicitly incorporating constraints in control law. MPC require an accurate plant model. The basis of the integration of machine learning and MPC in this work is the use of deep learning to learn an accurate plant model that would enhance the control capability of MPC. Using this strategy leverages the advantage of both machine learning and MPC and provides a robust mathematical architecture for control. The deep learning algorithm used in this work is the recurrent neural network (RNN) model.

In the development of the recurrent neural network model predictive controller (RNN-MPC) for the enhanced AGC system, a two-area power system is considered. Figure 1 shows the block diagram of a two area power system. Each area contains the components as shown in figure 1 in each area, all generators are assumed to be a coherent group.

Literature review

Nanda et al (2017) carried out work on automatic generation control of an interconnected hydrothermal power generation system on the basis of generation rate constraint. The key objective of the work was to achieve the load frequency control of the power system. The technique used is the proportional integral (PI) control. The work carried out included the modeling of the PI control loop to regulate the turbine governor to ensure the regulation of real power output. Simulations was used to validate the work. Result was obtained for controller set point following is 12.43%, for the frequency deviation is 0.47 and the Area Control Error (ACE) obtained is 0.52. The main merit of the approach used, as reported, was that it was simple to implement and achieved fairly god result in load frequency control. However, gaps in the work includes that

- The performance of the proposed AGC scheme experienced degradation with wide load variations and with incidences of contingencies (large load drops and transmission line outages) introduced into the power grid.
- The performance of the proposed controller showed inconsistencies with differences in load variation.

Concordia & Kirchmayer (2014) proposed a quadratic programming approach for Tie-line power flow and frequency control of electric power system. The purpose of the work was to assess the AGC performance using the quadratic programming approach as against using PI control approach. The work focused on the design of control structure that would ensure balance of frequency and tie-line in power system by regulating controlled outputs' area control error (ACE). The design revealed that relations between load frequency control (LFC) control variables and controlled outputs were given as constraints in quadratic programming objective function. From the analysis carried, the result obtained showing the effectiveness of the scheme was presented graphically. A graphical trend was given to show reduction in area control error (ACE) compared to using PID control. The graphical result presented showed that the projected quadratic control method showed improved reduction in ACE compared to the PI scheme. The scheme also showed better reduction in load frequency variation compared to the PI scheme.

It was shown that a major advantage of the proposed scheme is that it converged fairly quickly for two area interconnected power system. However a couple of gaps was observed in the work carried. The writers did not validate the proposed AGC solution under load variation and the scheme only worked well for one or two area interconnected power system. Furthermore, the new technique showed inconsistent result with multi area interconnected power system of more than two areas.

Kothari et al (2015) carried out work on automatic generation control of hydrothermal system. The algorithm used for the AGC solution is non-linear integer programming (NLIP). The work carried out entailed modeling the control structure for the control of hydrothermal turbine governor to regulate the active power output. Result from simulation carried showed about 32.6% percent overshoot in set point following. And turbine output power deviation of about 16.17%. The proposed approach has the merit of easy implementation, less memory footprint and quick convergence. The gap observed with the work is that the AGC scheme work was not validated for performance in generator out of set perturbation. Furthermore the impact of the generation control on economic dispatch was not validated.

M. L. Kothari, J. Nanda, and P. S. Satsangi (2015) proposed the use of mixed integer non-linear programming (MINLP) approach for automatic generation control of hydrothermal system with special consideration on generation rate constraint. In the work carried out, the AGC-hydrothermal generation system was performed as a mixed integer non-linear program problem, having generation output limit, turbine RPM as constraint in the controllers objective function. Simulations was used to validate the work. Result of from the validation of the work was presented graphically. Graphical trend showed slight deviation in load frequency, slight overshoot from generation power output set point. The authors reported improvement in comparison with the base power system's AGC system. However some gaps were observed. Worked was not evaluated for multi area power system. Controller performance was not validated for cases of sudden loss of generator unit within a generator group.

Solai & Kamaraj (2016) carried out work on Automatic Generation Control (AGC) problem of a deregulated power system using Adaptive Neuro Fuzzy controller. In the work carried out, the control structure of Hydro-Thermal generation in a multi area system (particularly three area) deregulated power system were considered in different operating conditions with non-linearities such as Generation Rate Constraint (GRC) and Backlash. In each control area, the effects of the feasible contracts (within the context of deregulation) were conducted as a set of new input signals in a modified traditional dynamical model. A combination of Neuro and fuzzy was the controller used to evaluate the frequency and tie-line feedbacks of the multi-source power system. Simulation was used to validate the work. Results of the new technique were evaluated with the Hybrid Particle Swarm Optimization (HCPSO), Real Coded Genetic Algorithm (RCGA) and Artificial Neural Network (ANN) controllers to illustrate its robustness.

The simulations were carried out for the dynamic response of the AGC system for large demand variations using HCPSO, RCGA, ANN controllers and the results were compared. The tie line power deviations for all the scenarios using the various controllers were obtained. The values showed that the tie line power exchange between the areas, ANFIS controller reached the exact exchange of power between the areas with minimum deviations compared to other controllers. Comparison for power deviation for the three scenarios with theoretical and the simulated values were obtained. Findings showed that the proposed ANFIS controller accomplished the regulation task very well in getting the same value as it gains in theoretical calculation. The plant parameters for three area deregulated power system used for modeling the control structure were obtained. The results showed that the proposed controller proved good dynamic performance over the others in terms of settling time, overshoot and undershoot. Also, the simulation results showed that the proposed ANFIS controller held good performance when compared to RCGA, HCPSO and ANN controllers for all possible contracts and for wide range of load disturbances. The authors reported that the main advantage of the strategy was its quick response to large load changes and disturbances in the presence of plant parameter discrepancy and system nonlinearities. Further benefits of the scheme as reported, was that the new technique is flexible with a simple structure that could be easy to achieve. Perhaps, the technique can be constructive for the real world power system. Although the work considered AGC in a deregulated power sector, the evaluations carried out did not reflect cost implications for using the proposed control scheme and also how it compares with the other considered AGC schemes.

In a deregulated environment, multi-source power generation that uses optimal output feedback controller was performed by **Parmar et al. (2014).** From the literature, the influence of physical constraints like time delay and generation rate constraint were not examined. **Gorripotu et al. (2015)** proposed a differential evolution algorithm optimized PID controller with derivative filter for an AGC with two area thermal system power system by considering generation rate constraint and time delay. Interline Power Flow Control (IPFC) was added in the tie-line to improve the system performance. To improve the system performance, Redox Flow Batteries (RFB) were included in area 1 along with IPFC. As a result, the system performance recorded a slight improvement. The authors did not consider bilateral constants.

Babu and Saibabu (2012) modified the traditional AGC with two area system. This was implemented in deregulated environment mainly to account for the effect of contracted and un-contracted power demands on system dynamics. The distribution companies (DISCO)'s concept of participation matrix (DPM) which was primarily aimed to simulate bilateral contracts was also recommended. Integral controller gain was optimized without considering generation rate constraint using integral squared error (ISE) technique. **Kumar et al. (2010)** and Garg and **Ilyas (2012)** reported similar work for thermal power system violating the constraints.

Nanda, Kothari, & Satsangi (2018) proposed a mixed integer non-linear programming (MINLP) approach for automatic generation control of an interconnected hydrothermal system in continuous and discrete modes considering generation rate constraints. What carried out involved the AGC of generators in an interconnected power system was modeled as a mixed integer non linear programming. Control objective function includes maximum generator RPM, power out limits of generators. Work was validated using simulations, result obtained in comparison with PID controller showed reduction in ACE for the interchange of power between areas in the interconnected power system. Reported merit of the proposed scheme was that it worked well with multi area interconnected power system. However it does not recover quickly to loss of generator in a generator groups. However gaps in the worked was observed. Worked did not take generation economic dispatch to consideration and impact of integration of controller with modern compensation devices like FACTS was not evaluated.

Hari, Kothari, & Nanda (2017) carried out work on the optimum selection of speed regularization parameter for automatic generation control in discrete mode with special consideration given to generation rates constraint (GRC). The algorithm used for the AGC system development is genetic algorithm with PID controller. Work carried out includes investigating proper selection R for interconnected reheat thermal-thermal system in continuous-discrete mode considering appropriate GRC (Generator rate constraint). Genetic algorithm was used to tune PID controller parameters for the regulation of generator speed parameters. Evaluation showed a reduction of 11.23% in generator speed deviation, a 8.95%

reduction in load frequency deviation compared with result obtained with PID control. The worked presented enhance algorithm for the use genetic algorithm for the tuning of PID controller parameters. However the controller was poor on compensating for erratic disturbance from load variation, which strongly impacts the coordination of generator groups. Further gaps in the research includes that the proposed AGC scheme did not integrate generation economic load dispatch. The performance of the proposed AGC scheme was not validated under generator outage contingencies.

A study on genetic algorithm based PID controller design for a multi-area AGC scheme in a restructured power system was carried out by **Bhongade et.al (2014)**. The authors proposed a multi-area Automatic Generation Control (AGC) scheme that would be suitable in a restructured interconnected power system with a proportional, integral and derivative (PID) controller in other to control the output of the generators. The PID controller parameters was tuned according to Genetic Algorithm (GA) based performance indices. The results obtained which were compared with the conventional controller showed that GAPID controller performed better than the conventional PID controller. The proposed genetic algorithm based PID controller obtained ACE of 13.14% lower than that of PID controller. In terms of merits, the work properly elaborated the structure of the control system for multi area interconnected power system and simplified the design specifications for the control of tie line power interchanges between areas in the power system. However, the authors did not evaluate the effect of abrupt inter area power interchange on the stability of the power system. Furthermore the proposed AGC system did not include generation economic dispatch in the modeling of the proposed control system.

Sabahi et.al (2018) carried out work on an Intelligent Automatic Generation Control with Two Area Interconnected Power System using feedback error learning (FED). The work performed by the authors centered on a new adaptive controller based on unsupervised learning approach, called feedback error learning (FEL) for automatic generation control. In this technique, the feed forward and feedback controller were used to simultaneously control the process. Also, dynamic neural network (DNN) was used as feed forward controller. Result obtained was presented graphically. Result obtained graphically showed substantial reduction in ACE, reduction in load frequency deviations compared to PID AGC control system. The merit of the work, as reported by the authors, is that the proposed design simplified the abstraction of linking power interchanges between areas with turbine governor control and load frequency control. Furthermore, the algorithm converged quickly with two area interconnected power system. However, the are gaps in the research. The authors did not consider generation economic dispatch in the modeling and training of the proposed intelligent AGC system.

Furthermore, the propose control scheme was not validated under loss of generator contingency.

Chown et.al (2015) carried out work using a Fuzzy Logic Controller for Automatic Generation Control (AGC). The work carried out by the authors involved designing of a fuzzy controller as part of the Automatic Generation Control system. The authors laid out the challenges that were associated with the AGC and secondary frequency control. Also discussed were the problems associated with the optimization of the original standard AGC controller, the design, implementation and optimization of the fuzzy controller. In the work carried out, the fuzzy controller was integrated into the existing AGC system with only a few modifications. Simulations was used to validate the work. Results were graphically presented. Improvement in transient response was reported. Compared to PID, proposed technique showed reduction in frequency and tie-line power deviations respectively. The authors did a good work in carrying out simulations for different scheduled generations under different normal loading conditions with step load disturbance in either different areas. A number of research gaps can be pointed. Considering that different type of turbines was considered in the AGC, the work did not validate peak deviations in frequency and tie-line power. Furthermore economic dispatch was not integrated in the controller specification.

Nanda et. al (2014) proposed Automatic Generation Control of an Interconnected Hydro-Thermal System Using Conventional Integral and Fuzzy Logic Controller. Authors carried out work on AGC system for Hydro-thermal system. In the work carried out, effects of variation of sampling time period on dynamic responses were investigated with conventional integral controller and fuzzy logic controllers. This was not without considering small step perturbations. Also investigated was the effects of different number of triangular membership functions and inputs for Fuzzy Logic Controller on dynamic response. Also, dynamic responses under small step perturbation were compared with consideration to integral and fuzzy logic controllers. Result obtained from validation carried out showed the hybrid control system for AGC proposed outperformed the conventional integral and the fuzzy logic controller. Graphical resulted presented showed the propose AGC system reduced frequency deviation, tie-line power deviation and reduced the ACE. The merits of the work, as reported, include contribution in the mixed integration of hydro and thermal turbines in same and in different areas of the interconnected power system. However, the authors did not indicate how the fuzzy rules can be dynamically adjusted to respond to stochastic variation in generation load curve. The authors did not integrate economic load dispatch in the synthesis of the fuzzy inference rules. Furthermore, the propose AGC system was not validated under loss of generator contingency and large load drops.

Kumar et. al (2014) used Particle Swarm Optimization(PSO) based Fractional order Proportional Integral Derivative(PID) control for the design of automatic generation controller for two-area power system. Work was carried out for the development of Fractional order PID controllers, considering particle swarm optimization (PSO) for Load Frequency control of two-area inter connected power system. The authors used simulations for the validation of the proposed AGC scheme. For the evaluation carried out, the dynamic response of the system was obtained for 1% and 10% step load perturbation (SLP). The work has the merit that the PSO design and its integration with PID was substantially elaborated with robust specification of the structure of particle velocity. However, the convergence of the algorithm was slow. Furthermore gaps in the research carried out were:

- The work did not evaluated the effect of abrupt inter area power interchange on the stability of the power system.
- the proposed AGC system did not include generation economic dispatch in the modeling of the proposed control system.

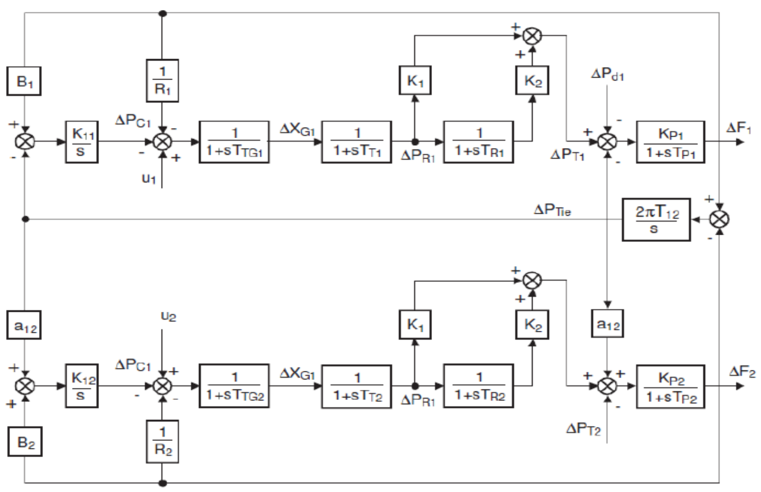

Figure 1: Block diagram of two-area power system.

The nomenclature used in the diagram and the nominal parameter values are given as follows:

$\Delta f_i(t)$: Incremental frequency deviation in Hz

$\Delta P_{Ti}(t)$: Incremental change in the ith subsystem's output in pu MW

$\Delta P_{Ri}(t)$: Incremental change in the output energy of the ith reheat type turbine in pu MW

$\Delta P_{Ci}(t)$: Incremental change in the integral controller

$\Delta P_{Tie}(t)$: Incremental change in the tie-line power

$\Delta P_{di}(t)$: Load disturbance for the ith area in pu MW

$u_i(t)$: Output of the automatic generation controller for ith area

T_{Gi}: ith Governor time constant in s

T_{Ti}: ith Turbine time constant in s

T_{Ri} : ith Reheat time constant in s

T_{Pi}: ith Subsystem-model time constant in s

K_{Pi} : ith Subsystem gain

K_{Ij} : ith Subsystem's integral control gain

B_i: ith Subsystem's frequency-biasing factor

K_i: The ratio between output energy of the ith stage of turbine to total output energy

R_i: Speed regulation for i th subsystem due to the ith governor action in Hz/pu MW

T_{ij}: Synchronizing coefficient of the tie-line between ith and jth areas

a_{12}: The ratio between the base values of two areas

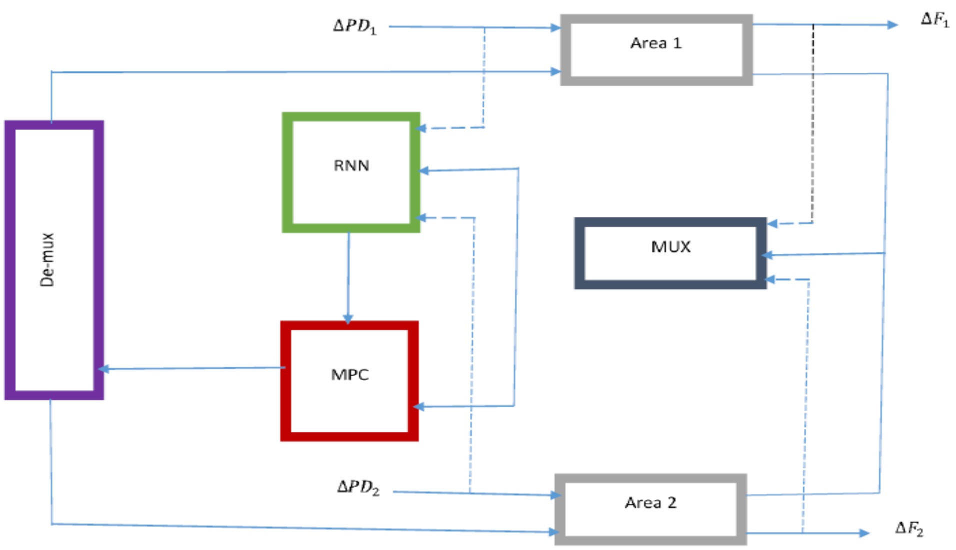

Figure 2: Block diagram of RNN-MPC controller design.

The RNN uses machine learning to learn the model of the plant (the power system). The learnt plant model (in the state space form) is input to the MPC process. The inputs to the deep learning process (the RNN) are the frequency deviations in area 1 (ΔF_1), frequency deviations in area 2 (ΔF_2), load change in area 1(ΔPD_1), load change in area 2 (ΔPD_2), and tie-line power deviation (ΔP_{12}).

Take the plant model learnt via machine learning to be of the state space form:

$$X(k+1) = Ax(k) + Bu(k) \qquad (3.17)$$

$$y(k+1) = Cx(k) + Du(k) \qquad (3.18)$$

$$U(k) = [u(K|k), u(k+1|k), \dots, u(k+Nc-2|k), u(k+Nc-1|k)] \qquad (3.19)$$

Where, $x(k) \in R^n$ is the state vector at the moment k, $x(k+p|k) \in R^n$ are the predicted state vector for the future time $(k+p)$. N_c Represents the control horizon (i.e. number of control moves) and the notation $u(k+p|k)$ indicates that the control signal to the generator units speed governor (prediction of the control input value) for the future time $(k+p)$ is calculated at time k. The control inputs are calculated in order to ensure that the difference between the predicted controlled output $y(k+p|k)$ (in this case the, frequency and tie-line power flow) and the anticipated set of points $r(k+p|k)$ (the predicted load reference setpoint at the future time $(k+p)$) for the outputs are reduced, over the prediction limit/horizon N_p $(p = 1,2 \dots.., N_p)$ The prediction horizon is the number of the predictions). It is important to know that only the first element from the calculated control inputs is applied to the generator governor unit, i.e. $u(k) = u(k|k)$. The fundamental control strategy for the proposed AGC system is that the MPC uses the RNN learnt model of the power system to predict the future output $y(k+p|k)$ (frequency and tie-line power) of the interconnected power system for the prediction horizon Nc given the future control inputs (engine governor control signal). Moving over to the next sample time$(k+1)$, a new measurement of the process outputs occurs and the entire process is repeated. At each step of the algorithm, the length of the control and prediction horizon is not only kept same, but then shifted for one value forward (the principle of the receding horizon). In the plant state space model, the system matrices include A; B; C; D; (i.e. power system model parameters). In this work deep learning is used to automatically learn these system matrices.

The trajectory of control input over the control horizon of power systems is determined in the predictive algorithms on the basis of the RNN learnt plant model, by reducing a cost function (i.e. objective function). Generally, the cost function comprised of two parts. Part one represents the differences between the load reference setpoints and the predicted outputs (power system frequency and tie-line power). This is referred to as the cost of predicted control errors. Then, part two represents the consequences for the changes of the control value.

The cost function used in this work for the MPC optimization computation is the quadratic cost function, given as (Backley White et al, 2018):

$$J(K)=\sum_{P=1}^{N_p} \|y(k+p|k)-r(k+p|k)\|_Q^2 + \sum_{P=1}^{N_p} \|\Delta u(k+p|k)\|_R^2 \qquad (3.20)$$

Where

$\Delta u(k+p|k) = u(k+p|k)-u(k+p|k-1)$; Q and Rare two tunable matrix weights.

The idea is to use one function not only to minimize the output errors, but is a way to keep the changes of the control value at the minimum. Other notation in equation is obvious.

1. Design of RNN for the deep learning of plant model

Referring to figure 3, the core of the proposed control system is the use of machine learning algorithm to dynamically learn the model of the power system. This model is what is used (by the MPC) to generate the control signal to the generator engine governors. The key control structure is based upon integrating a number of statistical methods which sample the control area behaviour and infer model of the generation outputs and the load deviations in the power system. For such data-driven strategy to be effective, an objective function is required with local maxima that corresponds to the generation and load swings in the power system.

Network structures, like what is obtainable with RNN, are sometimes called Finite Impulse Response (FIR) digital filter or Infinite Impulse Response (IIR) digital filter (Back, D. & Tsoi, A. C, 1993; Wan, E. A, 1996). The problem of designing a neural network architecture consists of choosing, e.g., the number of layers, the number of neurons in the hidden layers, and the appropriate interconnections in a multi-layer perceptron(MLP), or setting more complex parameters in the network. Network performance can dramatically change when such parameters are modified. The RNN modeled here consists of a globally feedforward structure (i.e., synapses connect only a layer k with the layer k (k + 1)) characterized by taps and feedback connections in each synapse. The following notation (Campolucci et al, 1999) is used here:

M number of layers in the network.

K layer index. In particular, k = 0 and k = M denotes the input and the output layer, respectively.

N_k number of neurons of the kth layer.

n neuron index.

$x_n^{(k)}(t)$ output of the nth neuron of the kth layer. In particular, n = 0 refers to the bias input: $x_0^{(k)} = 1$.

The input signal is $\{x_n^{(0)}\}$, n = 1, …, N_0.

$L_{n,m}^k$ number of delays of the synapses of the nth neuron of the kth layer relative to the mth output of the (k – 1)th layer.

$I_{n,m}^k$ number of feedbacks of the synapses of the nth neuron of the kth layer relative to the mth input of the kth layer.

$w_{n,m(p)}^k$ (p = 0, 1, 2, … $L_{n,m}^k - 1$) coefficients of the FIR synapse. If $L_{n,m}^k = 1$, the synapse has no delays. w_{n0}^k is the bias.

$v_{n,m(p)}^k$ (p = 0, 1, 2, ...$L_{n,m}^k - 1$) coefficients of the IIR synapse. If $I_{n,m}^k = 0$, the synapse is a FIR filter.

sgm(s) activation function.

$y_{n,m}^k(t)$ synaptic filter output at time t relative to the synapse of the nth neuron, kth layer and mth input.

$s_n^k(t)$ "net" function relative to the synapse of the nth neuron, kth layer.

$d_n(t)$ (n = 1, …, N_M) desired output sequence at time t.

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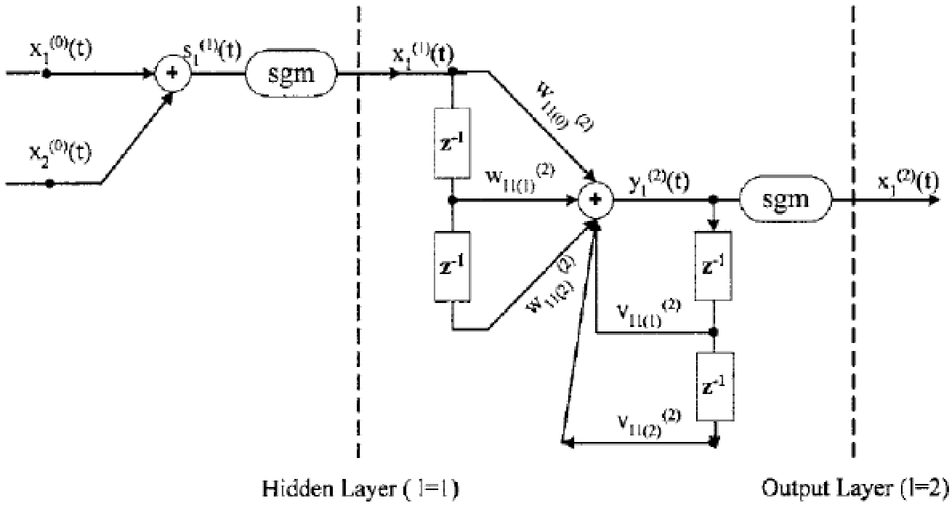


Figure 3: Structure of the recurrent neural network.

The time revolution of neuron n belonging to the layer k at sample t is described by the following three equations:

$$y^k_{n,m}(t) = \sum_{p=0}^{L^k_{n,m}} w^k_{n,m(p)} \cdot x^{k-1}_{n,m}(t-p) + \sum_{p=1}^{L^k_{n,m}} v^k_{n,m(p)} \cdot v^k_{n,m}(t-p), \qquad (5)$$

$$s^k_n(t) = \sum_{m=0}^{N_{k-1}} y^k_{n,m(t)}, \qquad (6)$$

$$x^k_n(t) = sgm[s^k_n(t)]. \qquad (7)$$

1.2 The learning algorithm

In the application of machine learning, proper training of a neural network is the most important aspect of making a reliable model (et al, 2019). In this work both historic and artificial generated data set containing power generation schedule, generation dispatch, power flow, load schedule and load demand, load variations, load disturbance and frequency deviation time series would be used to train the deep recurrent neural network. The training essentially entails fine-tuning the weights of the neural network based on the error rates obtained in the previous epoch (i.e. iteration). Proper tuning ensures lower error rate, making the model reliable by increasing its generalization. The training algorithm used in the simulations carried out in this work is the Causal Recursive Back Propagation (CRBP) algorithm. Following derivation shows relations of the error rate, learning rate and how the CRBP relates to and is extracted from the Recursive Back Propagation (RBP) algorithm.

The instantaneous global error at time t is defined as

$e^2(t) = \sum_{n=1}^{N_M} e_n^2(t)$ (8)

With

$e_n(t) = d_n(t) - x_n^M(t)$ (9)

So, the global error over the training epoch is

$E^2 = \sum_{t=l}^{T} e_n^M(t)$, (10)

Where T is the duration of the training epoch.

The following definition is made:

$e_n^k(t) = -\frac{1}{2}\frac{\partial E^2}{\partial x_n^k(t)}$ (11)

And

$\delta_n^k(t) = -\frac{1}{2}\frac{\partial E^2}{\partial s_n^k(t)} = e_n^k(t).\,sgm[s_n^k(t)]$. (12)

Therefore, using the chain rule:

$$\Delta w_{nm(p)}^k = \sum_{t=l}^{T} \Delta w_{nm(p)}^k(t+1) = -\frac{\mu}{2}\frac{\partial E^2}{\partial s_{nm(p)}^k}$$

$$= -\frac{\mu}{2}\sum_{t=l}^{T}\frac{\partial E^2}{\partial s_n^k(t)}\cdot\frac{\partial s_n^k(t)}{\partial w_{nm(p)}^k} = \mu\sum_{t=l}^{T}\delta_n^k(t)\,.\frac{\partial s_n^k(t)}{\partial w_{nm(p)}^k}, \text{(13)}$$

Where μ is the learning rate. Similarly, the δ rule for the v weight is:

$$\Delta v_{nm(p)}^k = \sum_{t=l}^{T} \Delta v_{nm(p)}^k(t+1) = -\frac{\mu}{2}\frac{\partial E^2}{\partial w_{nm(p)}^k}$$

$$= -\frac{\mu}{2}\sum_{t=l}^{T}\frac{\partial E^2}{\partial s_n^k(t)}\cdot\frac{\partial s_n^k(t)}{\partial v_{nm(p)}^k} = \mu\sum_{t=l}^{T}\delta_n^k(t)\,.\frac{\partial s_n^k(t)}{\partial v_{nm(p)}^k}, \text{(14)}$$

Considering that

$\frac{\partial s_n^k(t)}{\partial w_{n,m(p)}^k} = \frac{\partial y_{nm}^k(t)}{\partial w_{nm(p)}^k}$ and $\frac{\partial s_n^k(t)}{\partial v_{n,m(p)}^k}\frac{\partial y_{nm}^k(t)}{\partial v_{nm(p)}^k}$,

This is obtained:

$$\frac{\partial s_n^k(t)}{\partial w_{n,m(p)}^k} = x_m^{k-1}(t-p) + \sum_{r=1}^{l_{n,m}^k} v_{nm(r)}^k\frac{\partial s_n^k(t-r)}{\partial w_{nm(p)}^k}, \quad \text{(3.31)}$$

$$\frac{\partial s_n^k(t)}{\partial w_{n,m(p)}^k} = y_m^k(t-p) + \sum_{r=1}^{l_{n,m}^k} v_{n,m(r)}^k\frac{\partial s_n^k(t-r)}{\partial v_{nm(p)}^k}.$$

Using the chain rule, it is possible to obtain:

$$e_n^k(t) = -\frac{1}{2}\frac{\partial E^2}{\partial x_n^k(t)} = \sum_{q=1}^{N_{l+1}}\sum_{k=1}^{T} -\frac{1}{2}\frac{\partial E^2}{\partial s_q^{k+1}(t)}\frac{\partial s_q^{l+1}(k)}{\partial x_n^k(t)}\ for\ k < M.$$

$$e_n^k(t) = \begin{cases} e_n(t) & for\ k = M, \\ \sum_{p=0}^{T-t}\sum_{q=1}^{N_{k+1}}\delta_q^{k+1}(t+p).\frac{\partial y_{q,n}^{k+1}(t+p)}{\partial x_n^k(t)} & for\ k = (M-1), \ldots, 1, \end{cases} \quad \text{(15)}$$

Where

$$\frac{\partial y_{q,n}^{k+1}(t+p)}{\partial x(t)_n^k} = \sum_{r=1}^{\min(I_{q,n}^{k+1},p)} v_{q,n(r)}^{(k+1)} \frac{\partial y_{q,n}^k(t+p-r)}{\partial x_n^k(t)} + \begin{cases} w_{q,n(p)}^{k+1} & if\ 0 \le p \le L_{q,n}^{k+1}-1, \\ 0 & otherwise. \end{cases} \quad (16)$$

These expressions constitute the RBP algorithm. As it can be noted the exact RBP algorithm is noncausal, since the e_n^k at time t depends on δ_q^{k+1} quantities, taken at future time instants. Therefore, the weight update can only be performed in batch mode. If a casualization is desired, a truncation of the future convolution is necessary. The truncated formula is, therefore,

$$e_n^k(t) = \begin{cases} e_n(t) & for\ k = M, \\ \sum_{p=0}^{Q_{k+1}} \sum_{q=1}^{N_{k+1}} \delta_q^{k+1}(t+p).\frac{\partial y_{q,n}^{k+1}(t+p)}{\partial x_n^k(t)} & for\ k = (M-1), \dots, 1, \end{cases} \quad (17)$$

Where Q_{k+1} is properly chosen.

The weight changes can be adjusted introducing a suitable number of delays D_k in the weight adaptation formulas in order to remove the noncausality:

$$w_{n,m(p)}^k(t+1) = w_{n,m(p)}^k(t) + \Delta w_{n,m(p)}^k(t+1-D_k), \quad (18)$$

$$v_{n,m(p)}^k(t+1) = v_{n,m(p)}^k(t) + \Delta v_{n,m(p)}^k(t+1-D_k), \quad (19)$$

Where

$$D_k = \begin{cases} 0 & if\ k = M \\ \sum_{i=k+1}^{M} Qi & if\ 1 \le l < M \end{cases} \quad (20)$$

This algorithm is the CRBP. It has some advantages with respect to RBP, one is which is that it can be efficiently implemented on-line.

It is worth nothing that, denoted with T the epoch dimension, Q_k is subject to the constraint $Q_k \in [0, T - t]$. considering the deduction of the Back & Toi algorithm (Back & Tsoi, 1993) for $Q_k \rightarrow 0$. In this case the learning algorithm is simpler, since expression (2) is now replaced by

$$e_n^k(t) = \begin{cases} e_n(t) & for\ k = M, \\ \sum_{q=1}^{N_{k+1}} \delta_q^{k+1}(t).w_{qn(0)}^{k+1} & for\ k = (M-1), \dots, 1, \end{cases} \quad (21)$$

The errors are back-propagated only through the weights $w_{nm(0)}^{k+1}$ of each synapse. Figure 4. shows the flow chart describing the modeling the deep learning Model Predictive control for AGC systems. Figure 5 shows flow chart for the CRBP algorithm for the training of the RNN.

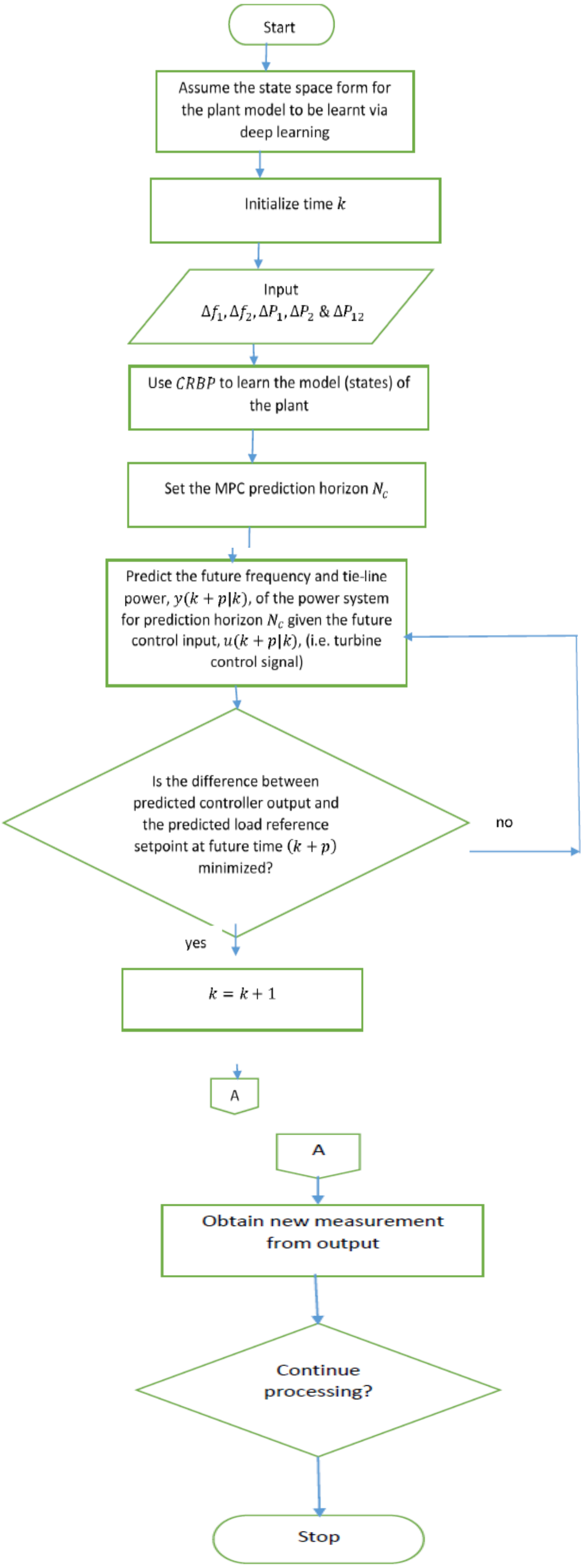


Figure 4: Flow chart describing the modeling the deep learning Model Predictive control for AGC systems.

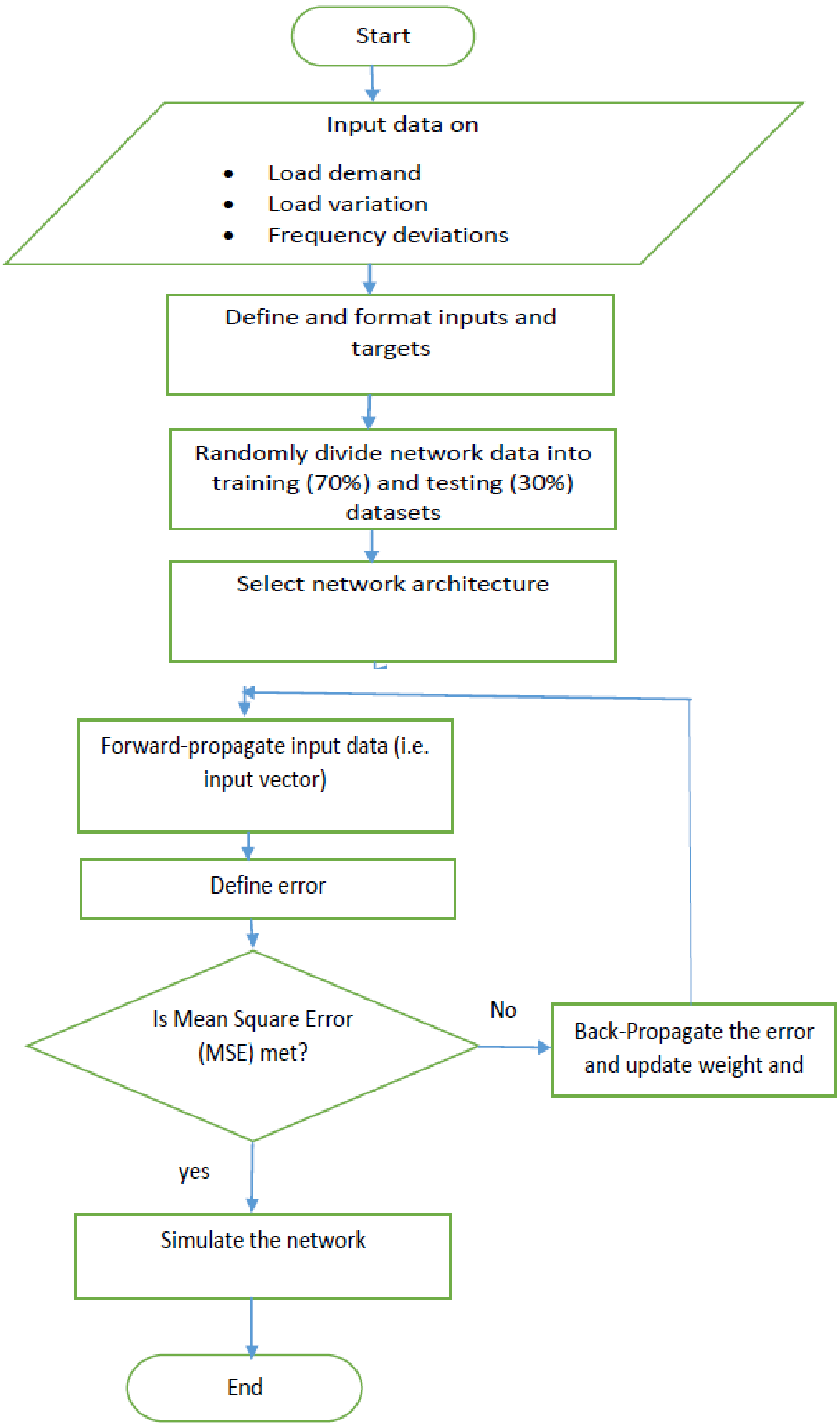


Figure 5: Flow chart for the CRBP algorithm for the training of the RNN.

2.0 Deep Learning model MPC for regulating tie-line power exchange for enhanced power balance in the controlled areas

In this work the RNN-MPC machine learning is trained to reduce power imbalance in the controlled areas. The model is trained to generate turbine governor control signal that reduces power imbalance. That is the model is specifically trained to modulate the settings of each turbine governor unit in order to reduce or eliminate power imbalance in the controller areas in the interconnected power system.

The input data set for the training and tuning of the deep learning model consists of area control error for area 1 (ACE1), area control error for area 2(ACE2), speed regulation R , governor time constant T_G, power system time constant T_p and load changes in area 1and 2 (ΔPD_1) and (ΔPD_2) respectively. This control structure is depicted in the block diagram of figure 6.

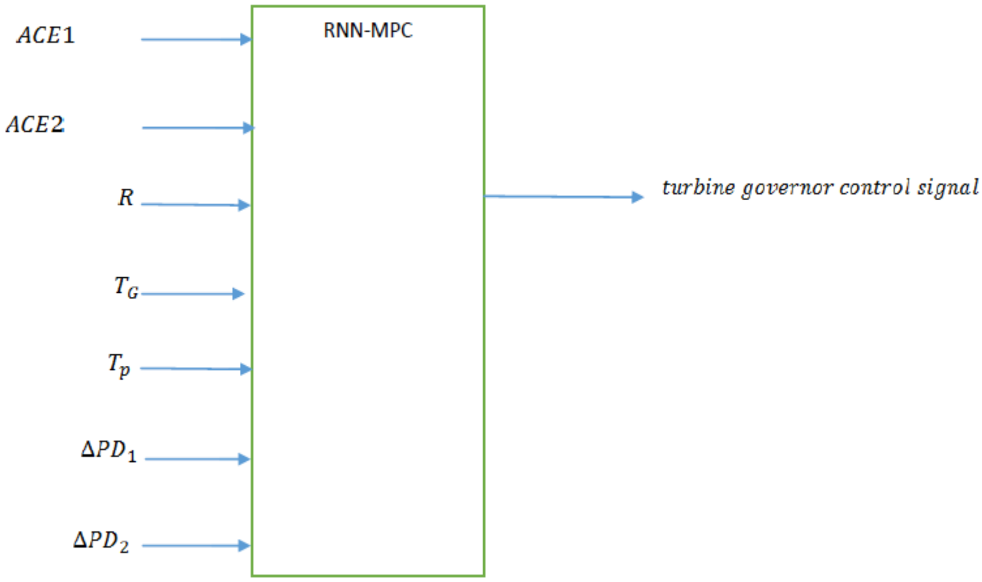


Figure 6: Parameters of the training input data set and output control signal of the deep neural network MPC for controlling power balance in the interconnected power system.

The key objective here is to train the RNN-MPC to output control signals to the generating units in each controlled area for the purpose of ensuring power balance in the interconnected power system. However, this work also considers the use of FACTS devices to ensure power balance in the controlled areas by controlling the power flow in the interconnecting tie-line. This essentially entails integrating the proposed AGC system and FACTS devices to achieve the power balance hence enhancing the stability of the power system.

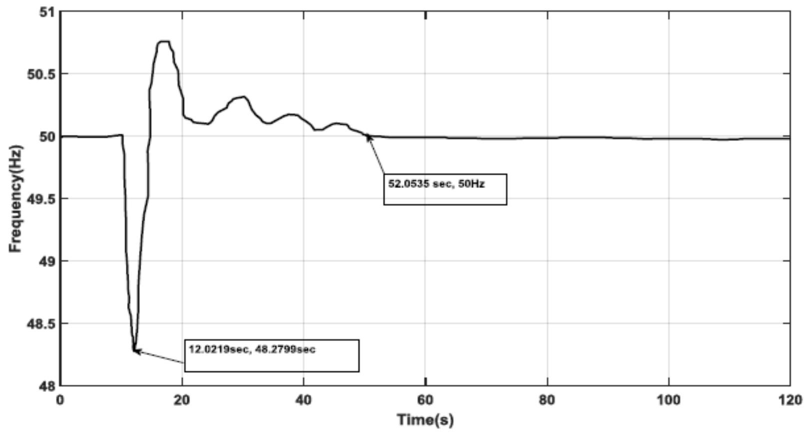


Figure 7: System frequency response with the RNN-MPC AGC system.

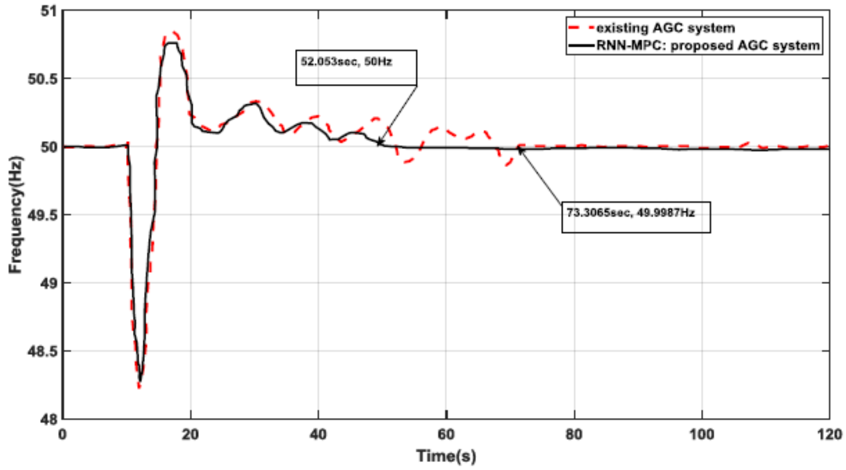


Figure 8: The frequency response for the 5% load change for the proposed deep learning AGC system and the existing AGC system.

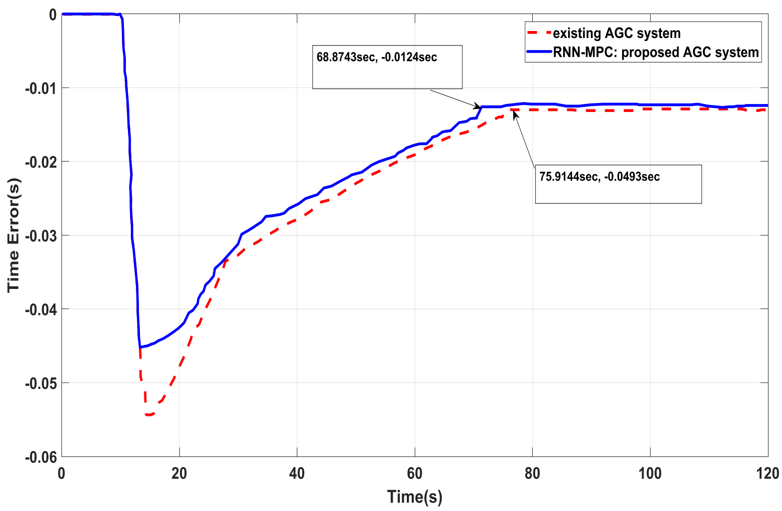
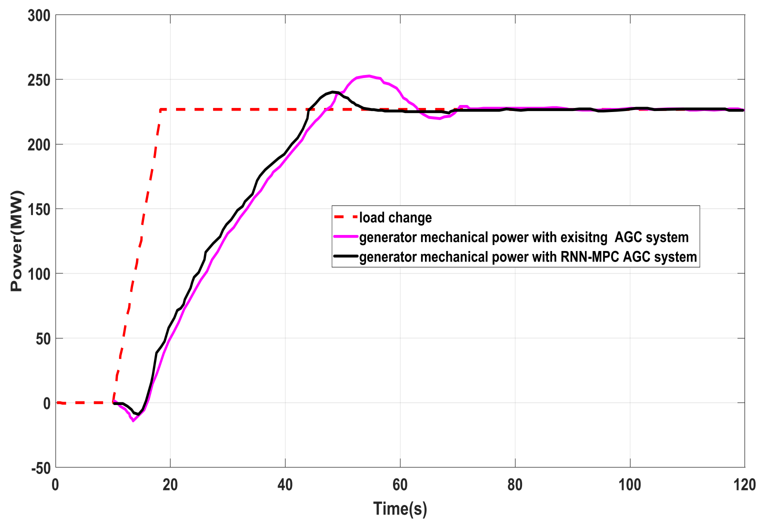


Figure 9: Comparison of the Time error of the power system using the existing with the proposed AGC systems.



CONCLUSION

The graphs clearly shows that the RNN -MPC took a shorter time than the base AGC system of the power system to restore the system frequency to the nominal value following the load disturbance. It is very important to return the power system to the nominal frequency in a very short time. Understand that the power system has substations, loads, control elements, relays (frequency relay: under frequency, over frequency etc. relays) that may react inappropriately, if the deviation of the frequency from normal operating value persists beyond certain thresholds. This inappropriate reactions from either frequency sensitive loads (that may trip off), certain generators (that might trip based on protection reactions initiated by local generator protection relays), substation intelligent electronic devices (IED) etc. may lead to cascaded mis operation that might lead to total frequency collapse in the power system.

Just like in the case of the base power system, when the system was subjected to the 5% load change, there was an initial drop in the generator output mechanical power. The drop in the generator output power was first sensed by the generator speed governor which initiated primary control in order to adjust the power generation output. The RNN-MPC AGC system acted to return the system to a state of balance between power generation and load demand. Generation was controlled resulting in achieving balance between power generated and load demand at about 53.217 seconds. This means it took about 43.2148 seconds for the power system to rebalance the power generation with load following the load disturbance. Recall that in the base case characterized, it took the power system about 61.9516 second to rebalance generation with load following the load disturbance. Furthermore, in the case of the

RNN-MPC AGC system, prior to achieving the generation load balance, the overshoot is about 12.8792MW. Whereas in the case of the existing AGC system, the overshoot is about 25.4165MW. The proposed controller achieved lower overshoot compared to the existing controller in the process of matching the power generation to the load. These results indicate that the proposed AGC system reduced the time taken to achieve rebalance of the load with the power generation following a load perturbation by almost 30.25%. The proposed AGC system also reduced the generation–load rebalancing controller overshoot by about 49.3274%.

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