Nonlinear Auto-Regressive Moving Average (NARMA-L2) Controller Design for UPFC

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Abstract: - Unified Power Flow Controller (UPFC) is considered as the most of powerful controller among all the Flexible AC Transmission System (FACTS) technology. It is selected in this study to obtain better utilization and controlling of power over the transmission network. UPFC has the capability of controlling the transmission line parameters and consequently the flow of the active and reactive power in the transmission line. The controllers which are being used in UPFC are very important to control the transmission lines parameters as desired. Artificial intelligence methods such as the neural network can be adopted in such application to identify and control nonlinear dynamic systems as desired. Regardless of the complication of the system, this type of controller will be successfully used to improve its control approach. In this paper, an adaptive control scheme based on a Nonlinear Auto-Regressive Moving Average (NARMA-L2) is designed and investigated. This type of adaptive controller, which is based on Artificial Neural Network (ANN) concept, will be implemented in UPFC, and will be investigated to ensure its robustness, effectiveness and the capability to accommodate any sudden load change in the system of Single Machine to Infinite Bus (SMIB). In addition the dynamic performance of NARMA-12 will be compared with another type of adaptive controller scheme called Neural Network Model Predictive Control (NNMPC).

Key-Words: - FACTS, UPFC, NARMA-12, NNMPC, ANN, SMIB

1 Introduction

FACTS devices are considered as an innovative solution to utilize and control the transmission line. UPFC technology is selected to be studied in this paper as it is considered as one of the most important device in the FACTs devices family. It can control, independently or simultaneously, all parameters that affect the power flow on the transmission line such as the line voltage, impedance and load angle. Moreover, the controllers which are being used in UPFC are very important to control all those parameters as desired. The conventional PI controller being used in UPFC application has a challenge to solve the system problem during system disturbance and sudden load change. Accordingly, this type of controller will be replaced with an adaptive scheme called Nonlinear Auto-Regressive Moving Average (NARMA-L2) Controller. NARMA-L2 Controller is considered as an adaptive scheme based on Artificial Neural Network (ANN) concept. ANN is considered as a model of how the human brain works. A biological neural network is an essential part of human brain. It is a highly complex network with the ability to process huge amounts of information simultaneously. A biological neural network consists of the central nervous system, which includes the brain and spinal cord. Moreover, composed of peripheral nervous which contain neurons and pathways associated with sensory inputs and motor response outputs as illustrated below in Fig 1. [1]

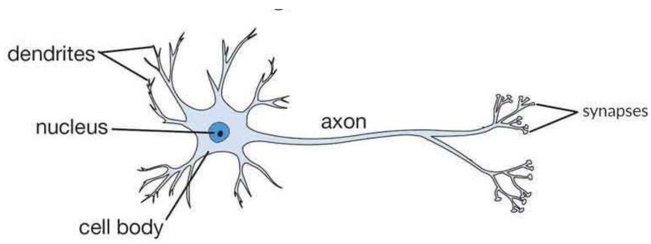

Fig. 1: Biological neuron

The input impulses travel via the sensory portion of the peripheral nervous system to the central nervous system for higher level interpretation to response and convey the action through the peripheral nervous system to relevant part in the human body. So, human brain contains of an enormous number of nerve cells and neurons. The combination of these cells is together creating a very complex network of signal transmission. Each cell collects inputs from all other neural cells it is connected to and if the collected cell information reaches a certain threshold, then it will be conveyed to all the cells it is connected to. The biological neural network compositions can be summarized as below:

1) Dendrites: receive electrical signals from other neurons.
2) Cell body: structurally contains of nucleus and organelles, but functionally processes the incoming signal from the dendrites.
3) Axon: part of the neuron that takes the electrical signals from the cell body to the pre-synaptic terminals.
4) Presynaptic terminals: Pre-synaptic terminals form the end of the axon where it junctions with another neuron at a specialized location called a synapse. A synapse is where the axon of one neuron communicates with the dendrites of another neuron.

So, the interconnection of the large number of neurons in the Biological neurons network architecture will allow a rapid communication spanning throughout all areas of the body. Although, Biological neural networks are complex, but Artificial Neural Network model will be basic structure representation as shown in Table 1. [2]

TABLE 1
Basic Structure of Biological Neuron

Structure	Function
Dendrites	Input
Cell body	Integration
Axon	Conduction
Pre-Synaptic terminals	Output

2 ANN Concept

ANNs, like human, learn by example. It can be trained after implementation and needs a trainer designed in hardware or software to provide punishments or rewards for the adopted weights. A reward is used for the correct response and lead to no further changes in the weights are required. A punishment indicated the network gave an incorrect response and the connection weight of the affecting neurons needs to be adjusted. Training after implementation is a continuous as long as the trainer is enabled. So, ANN is capable to learn and adapt in real time. Artificial Neural Networks (ANNs) and their learning capabilities have been examined for many decades. The most prominent feature of the neural networks their ability to learn from examples, using so called learning algorithms, they solve problems by processing a set of training data. basic computational element (model neuron) is often called a node or unit. It receives input from some other units, or perhaps from an external source. Each input has an associated weight ‘w’, which can be modified so as to model synaptic learning. The unit computes some function ‘f’ of the weighted sum of its inputs:

$$y_i = f(\sum_j w_{ij} y_j) \qquad (1)$$

Its output, in turn, can serve as input to other units as illustrated in Fig. 2.

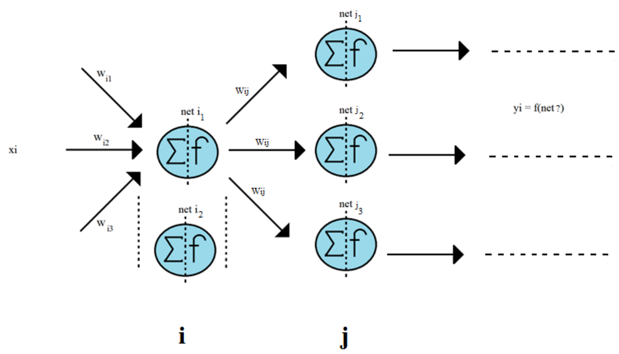

Fig.2: Artificial Neuron

The weighted sum $\sum_j w_{ij} y_j$ is called the net input to the ‘net’. Note that ‘wij’ refers to the weight from unit j to unit ‘i’ (not the other way around). The function ‘f’ is the unit's activation function as could be as shown in Table 2 (Larysa A. 2010).

TABLE 2
Artificial Neuron Activation Function

Function name	Formula	Values range
Linear	$F(S) = kS, k \in \mathbb{R}_+$	$(-\infty, \infty)$
Semi linear	$F(S) = \begin{cases} kS, S > 0, k \in \mathbb{R}_+ \\ 0, S \leq 0 \end{cases}$	$[0, \infty)$
Sigmoid	$F(S) = \frac{1}{1+e^{-\alpha S}}$	$(0, 1)$
Bipolar sigmoid	$F(S) = \frac{2}{1+e^{-\alpha S}} - 1$	$(-1, 1)$
Hyperbolic tangent	$F(S) = \frac{e^{\alpha S} - e^{-\alpha S}}{e^{\alpha S} + e^{-\alpha S}}$	$(-1, 1)$
Exponential	$F(S) = e^{-\alpha S}$	$(0, \infty)$
Sinusoidal	$F(S) = \sin(S)$	$[-1, 1]$
Fractional	$F(S) = \frac{S}{\alpha + \lvert S \rvert}$	$[-1, 1]$
Step	$F(S) = \begin{cases} 1, S \geq 0 \\ 0, S < 0 \end{cases}$	$[0, 1]$
Signature	$F(S) = \begin{cases} 1, S \geq 0 \\ -1, S < 0 \end{cases}$	$[-1, 1]$
Binary step	$F(S) = \begin{cases} -1, S \leq -1 \\ S, -1 < S < 1 \\ 1, S \geq 1 \end{cases}$	$[-1, 1]$

So, in the feed forward neural network the inputs are multiplied by the weights then will be summed in the neural cell where the result of the summation will also pass through the activation function 'f'. The outcome from the neural cell will be multiplied again with the next weights and the process will continue up until the final result is obtained. One the final result is obtained it will be compared with the actual result in order to determine the error and train the model. Back propagation will be used to train the network. An example will be extracted from Fig 2, in order to clarify the concept and the equation that will be used in the feed forward and back propagation method. So, for simplicity one string which is in green colour will be analyzed as illustrated in Fig. 3.

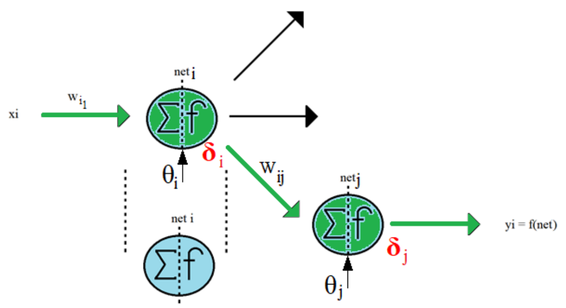

Fig. 3: Data flow in One String of Artificial Neuron

The calculation starts from the last output neuron all the way back to the input:

$$Y_j = f_j(f_i(X_i * W_{i1}) * W_{ij}) \quad (2)$$

$$\text{Error} = Y_{desire} - Y_j \quad (3)$$

$$\text{Gradient Error } (\delta_j) = \frac{\partial Yj}{\partial Xi} * \text{Error} \quad (4)$$

The output from neuron 'i' is:

$$Y_i = f_i(X_i * W_{i1}) \quad (5)$$

$$\text{Gradient Error } (\delta_i) = \frac{\partial Yi}{\partial xi} * (W_{ij} * \delta_j) \quad (6)$$

After getting the gradient error 1 and 2 from equation number (4) and (6) respectively, the ΔW and $\Delta\theta$ will be calculated in order to update the existing weights and biases.

$$\Delta W_{ij} = \text{learning Rate } (\alpha) * Y_i * \delta_j \quad (7)$$

$$\Delta W_{i1} = \text{learning Rate } (\alpha) * X_i * \delta_i \quad (8)$$

$$\Delta\theta_j = \text{learning Rate } (\alpha) * \theta_j * \delta_j \quad (9)$$

$$\Delta\theta_i = \text{learning Rate } (\alpha) * \theta_i * \delta_i \quad (10)$$

Hence, the ΔW and $\Delta\theta$ are obtained, the weights and biases will be updated as follows:

$$W_{ij} \leftarrow W_{ij} + \Delta W_{ij} \quad (11)$$

$$W_{i1} \leftarrow W_{i1} + \Delta W_{i1} \quad (12)$$

$$\theta_j \leftarrow \theta_j + \Delta\theta_j \quad (13)$$

$$\theta_i \leftarrow \theta_i + \Delta\theta_i \quad (14)$$

The next input will be introduced to the network and same procedure will be followed to obtain the outputs and correct the weights and biases.

3 UPFC Study

Gyupyi introduced the UPFC in 1991 [3]. It is composed of two voltage source converters linked by common d.c. link as illustrated in Fig. 4.

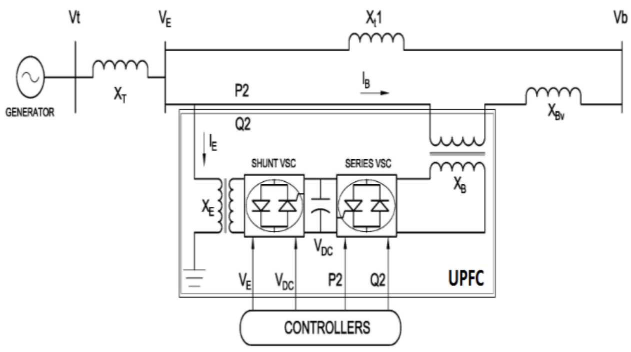

Fig.4. UPFC in SMIB

Both steady state and dynamic model will be needed for inspecting the performance of the UPFC in the system. The steady state model is used to determine the initial condition of the system. While, the dynamic model will be performed to ensure that the performance of the UPFC and its controllers during disturbance and any sudden load changes are acceptable and met the expectations.

A. Nabavi-Niaki and M. R. Iravani [4] model is considered in this study as illustrated in Fig. 5.

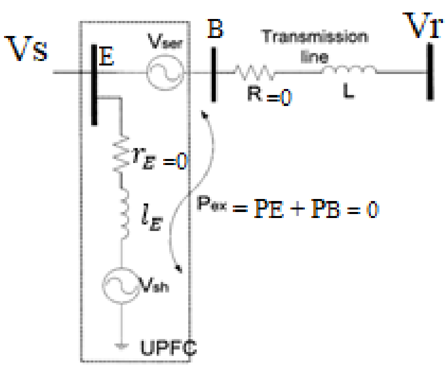

Fig.5. UPFC Decouple Model

In this approach, the UPFC is replaced by equivalent bus representation. The main role of the UPFC in steady state is to perform the power flow analysis and the result of the initial condition will be used to determine the required converter control variables used for the PWM strategy such as modulation index and phase angle. The UPFC was considered as a losses system by negating the coupling transformer resistance. Moreover, voltage sources are linked so that the total exchange UPFC power is equal zero.

$$\mathrm{P_{Et}} + \mathrm{P_{Bt}} = 0 \tag{15}$$

The injected voltage to the converters assumed to be a pure sin wave signals by neglecting the higher order frequency components formed due to switching. The UPFC dynamic model can be represented by the d.c. link dynamic model which composes of the series current, shunt current, modulation indexes and angles of both converters. The d.c. link dynamic model is determined as shown below.

$$\frac{d\upsilon_{dc}}{dt} = -\frac{3m_E}{4C_{dc}}\begin{vmatrix}\cos\delta_E & \sin\delta_E\end{vmatrix}\begin{vmatrix} i_{Ed} \\ i_{Eq}\end{vmatrix} + \frac{3m_B}{4C_{dc}}\begin{vmatrix}\cos\delta_B & \sin\delta_B\end{vmatrix}\begin{vmatrix} i_{Bd} \\ i_{Bq}\end{vmatrix} \tag{16}$$

m_E and m_E are the amplitude modulation ratios, while δ_E and δ_B are the phase angle of the voltage source converter control signal. m_E, m_E, δ_E and δ_B are selected to be connected to the control output signal to control V_E, Q_2 , V_{dc} and P_2 respectively.

4 System Study

The UPFC is incorporated in a Single Machine to Infinite Bus (SMIB) system to test and analysis the entire system performance. Model number 1.0 of a synchronous generator with IEEE ST1A excitation system will be adopted as it is used in most of the dynamic studies of power system such as the studied performed by M. Abido [5], M. Abido et al. [6] and S. A. Alqallaf [7]. Matlab platform will be used to perform the system simulation.

5 NARMA-L2 Control Design

5.1 The Concept of NARMA-L2 Controller

NARMA-L2 is considered as one of the most appropriate architectures for prediction and control of time variant nonlinear systems. It has the advantage of fast and accurate output regulation due to its mapping capability. NARMA-L2 control technique is based on input output linearization [7]. The principle of NARMA-L2 controller is to use linearization method in order to linerized the output for the new control input [8] and [9]. There are two basic steps in NARMA-L2 [10]:

5.1.1 System Identification

A neural network of the plant that needs to be controlled is developed using two sub networks for the model approximation as shown in Fig. 6.

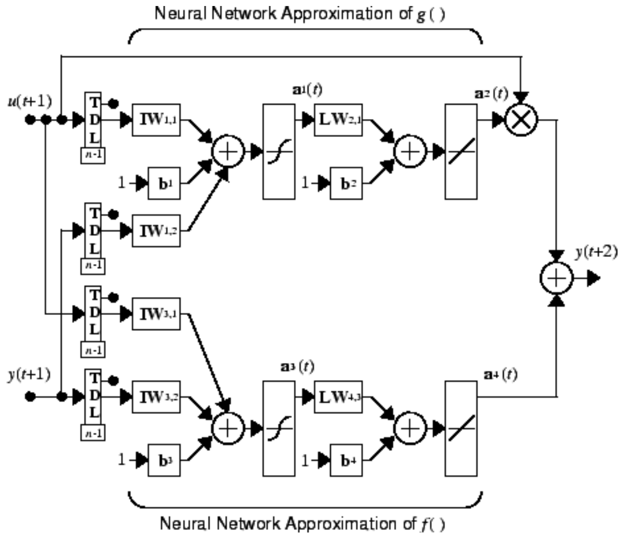

Fig.6. NARMA-L2 system Identification

The network is then trained offline in batch form using data collected from the operation of the plant. The discrete-time nonlinear system is represented by one standard model which is the Nonlinear Autoregressive Moving Average:

$$\boldsymbol{y(k+d) = N[y(k), y(k-1), \ldots, y(k-n+1), u(k), u(k-1), \ldots, u(k-n+1)]} \tag{17}$$

Where u(k) and y(k) are the system input output. 'm' and 'n' positive integers representing the number of measured delayed values of inputs and outputs respectively and 'd' is the relative degree. To maintain an acceptable performance, the number of the neural network hidden layer was selected to be 30 and 10000 numbers of training samples were used to train the neural network model.

5.1.2 Control System Design

The controller is simply the rearrangement of two sub-networks of the plant model which is 'g' and 'f' as illustrated in Fig. 7. The controller used is based on the NARMA-L2 approximate model. The solution proposed by Narendra and Mukhopadhyay [11], is to use approximate models to represent the system.

$$\mathbf{\hat{y}(k+d) = f[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-m+1)] + g[y(k), y(k-1), \ldots, y(k-n+1), u(k-1), \ldots, u(k-m+1)] \cdot u(k)} \tag{18}$$

This model is in companion form, where the next controller input u(k) is not contained inside the nonlinearity. The advantage of this form is that the control input that causes the system output to follow the reference y(k + d) = yr(k + d) can be solved. The resulting controller is of the form:

$$\mathbf{y(k+d) = f[y(k), y(k-1), \ldots, y(k-n+1), u(k), u(k-1), \ldots, u(k-n+1)] + g[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)] \cdot u(k+1)} \tag{19}$$

Using the NARMA-L2 model, the controller can be obtained as follows

$$\mathbf{u(k+1) = yr(k+d) - f[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)] g[y(k), \ldots, y(k-n+1), u(k), \ldots, u(k-n+1)]} \tag{20}$$

Which is realizable for $d \geq 2$. The NARMA-L2 controller block diagram is shown in Fig. 7.

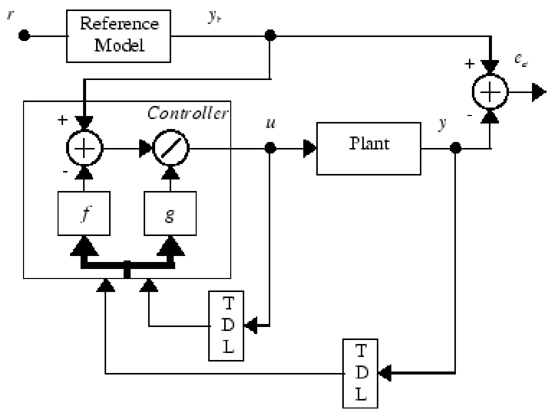

Fig.7. NARMA-L2 Controller

The real power in line 2 is considered as a reference signal which will be fed to the NARAM-L2. The output of real power in line 2 from the SMIB will be also fed to the NARMA-L2 in order to simulate and give the proper control signal to the plant as shown below in Fig. 8.

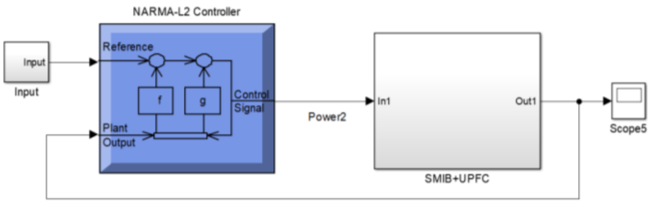

Fig.8. NARMA-L2 control configuration

5.2 NNMPC Concept Design

Model Predicative Control (MPC) is widely used approach which relies on solving a numerical optimization problem on line, but due to the complexity of nonlinear control problems it is in general necessary to apply various computational or approximate procedures for the solution. The main drawback of the MPC is that the optimization problem may computationally quite demanding for nonlinear systems. So, in order to reduce the on-line computational requirements, another approach is applied as off-line function approximations to represent the optimal control law such as artificial neural network. Two-layer networks, with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer, are universal approximations as illustrated in Fig. 9. The Neural Network Model Predictive Controller is based on the concept of the Artificial Neural Network. NNMPC uses a neural network model of a nonlinear plant to predict future plant performance.

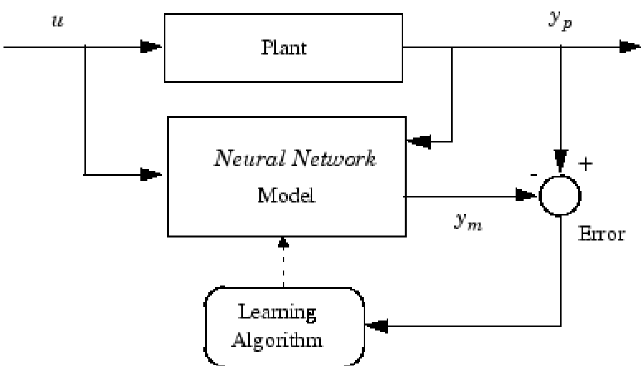

Fig.9. NNMPC System Identification

5.3 Dynamic Response Performance of NARMA-L2 Controller

5.3.1 NARMA-L2 Performance in Case of Sudden Step Change

Figures 10 to 13 show the dynamic performance of NARMA-L2 and NNMPC for the real power in line 2 (P_2), reactive power (Q_2), DC line voltage (V_{dc}) and terminal line voltage (V_{Et}) respectively. In this case, a sudden step change test (-10%) at time second number 15 has been done for the real power (P_2). It can be seen that, both types of controllers are efficient to stabilize the system. Table 3 shows that, the dynamic performance of NARMA-12 is slightly better than NNMPC in raising time and setting time. However, the overshoot percentage in case of NNMPC is better that that of NARMA-L2.

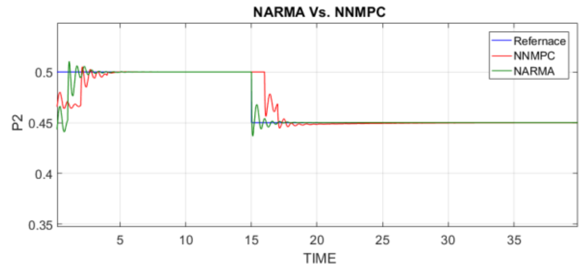

Fig.10: Real Power flow (P_2) in case of sudden step change (-10%)

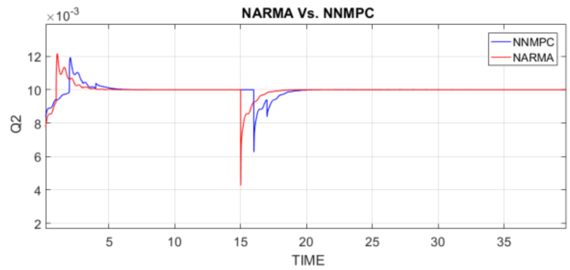

Fig.11: Reactive Power flow (Q_2) in case of sudden step change (-10%)

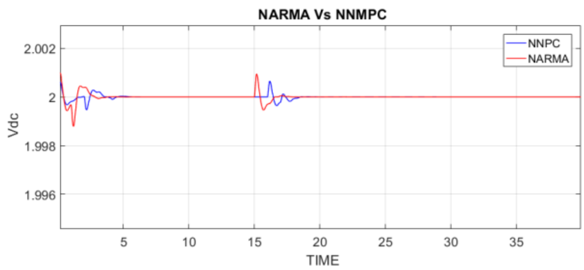

Fig.12: Dc Line Voltage (V_{dc}) in case of sudden step change (-10%)

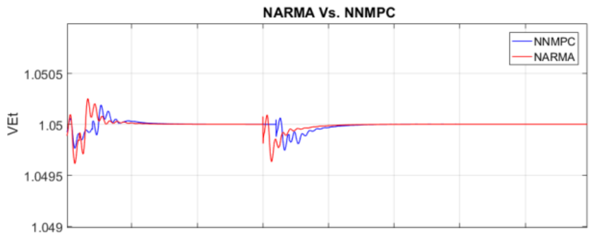

Fig.13: Terminal Voltage (V_{Et}) in case of sudden step change (-10%)

Table.3
Rating Score for each type of controller during (-10%) sudden step change for the real power P_2

	Rise Time (Sec.)	Settling Time (Sec.) (2%)	Overshoot (%)
NNMPC	2.09	3.6	0.54
NARAMA	0.07	2.24	1.96

In addition, it has been notice from Fig. 14 that, the 10% reduction in power flow in line 2 is diverted to line number 1 in order to meet the total load required which is equal to 1 p.u. So, the power flow maneuver is achieved in this case satisfactorily.

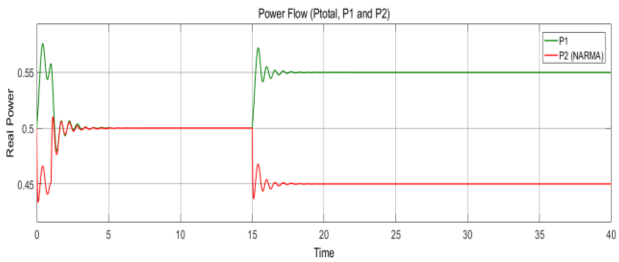

Fig.14. Real Power flow in line 1 and 2 by using NARMA-L2 in case of sudden step change (-10%)

5.3.2 NARMA-L2 Performance in Case of Sudden System Disturbance

Figures 15 to 18 show the dynamic performance of NNMPC and MPC for the real power in line 2 (P_2), reactive power (Q_2), DC line voltage (V_{dc}) and terminal line voltage (V_{Et}) respectively. In this case, a sudden system disturbance at time second number 70 has been done for the real power (P_2). It can be seen that, both types of controllers are responding to the system change satisfactorily. Table 4 shows that, the dynamic performance of NORMA-L2 is slightly better than NNMPC in raising time and setting time. However, the overshoot percentage in case of NNMPC is again better that that of NARMA-L2.

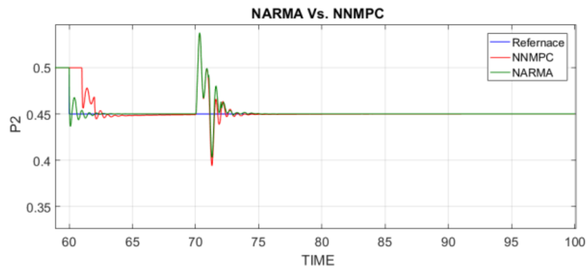

Fig.15: Real Power flow (P_2) in case of sudden system disturbance

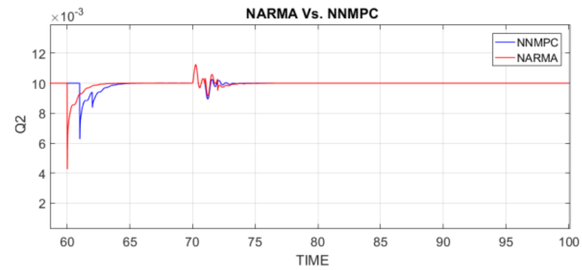

Fig.16: Reactive Power flow (Q_2) in case of sudden system disturbance

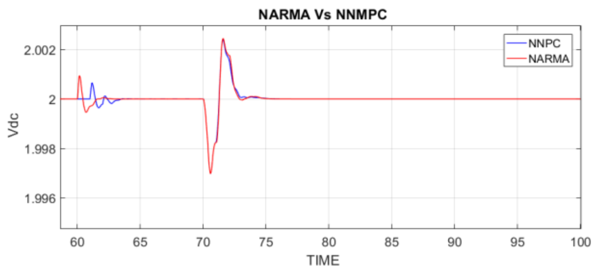

Fig.17: DC line voltage (V_{dc}) in case of sudden system disturbance

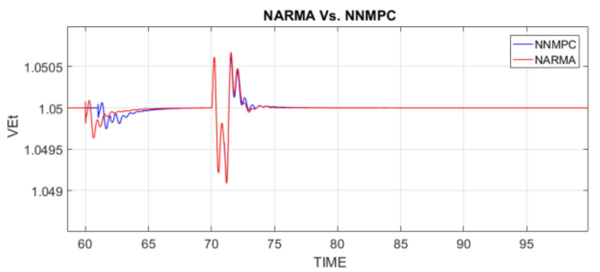

Fig.18: Terminal voltage (V_{Et}) Real Power flow (P_2) in case of sudden system disturbance

Table 4
Rating Score for each type of controller during disturbance for the real power P_2

	Rise Time (Sec.)	Settling Time (Sec.) (2%)	Overshoot (%)
NNMPC	1.11	2.26	19.2
NARAMA	1.15	2.31	19.4

6 Conclusion

The capability of controlling the system parameters in the transmission lines which consist of UPFC was verified and found that the steady state and dynamic behaviour of the power system was enhanced in presences of the UPFC and the adaptive controllers. The robustness, controllability and the effectiveness of the proposed adaptive controllers (NARMA-L2) has been proven. In addition, the proposed controller can perform faster in terms of rising time and settling time than the NNMPC. However, the overshoot percentage created with using NARMA-L2 controller is greater than NNMPC during sudden step change and sudden system disturbance.

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