Trajectory Based Damping of Electromechanical Oscillation

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Abstract- *This paper implies a trajectory based damping of electromechanical oscillations. Basically this is also done using model predictive control. This paper basically focuses on Model free learning method or Reinforcement Learning Method. It finds out the signals and superimposed to the existing controllers. Power system Stabilizer is used as a controller. The difference in damping proves Reinforcement learning as the best approach. This control is implemented on multiple or four generators.*

Keywords- Damping control, model predictive control, reinforcement learning, tree based learning.

I. INTRODUCTION

The power flows from sending end to receiving end. The power exchanges take place over long distance nowadays as a result expansion of interconnected grid system has been in use popularly. This also leads to the modern large scale electric power system. Some characteristics of modern large scale system like heavy loading and long transmission distances leads to sustained oscillations. This oscillation leads to threaten the system and leads to the failure of system. The model based approach is very easy. It basically identifies the oscillation modes and then damps the oscillations. It is purely mathematical approach. It is based on transfer function model, framing the state space equations which predict the next suitable state of system. However, a new power flow control device makes the system complex and it questions its robustness also. The new approach which is RL. It is model free learning approach. It produces a inputs which gets superimposed on existing controller like power system stabilizer and improve the damping process.

In this respect, this paper proposes a trajectory based approach to damp the oscillations. The output generated is feedback to generate an error and it is fed to power system stabilizer and made as a switch. The excitation block selects the most suitable switch from the three switches and stabilizes the system and improves the damping. The four parameters to be controlled: Maximum voltage, sequence voltages, Line power and rotor angle.

The rest of the paper is organized as follows: Section II describes the trajectory based approach by model free learning method. Section III describes the sub model diagram of Reinforcement Learning method. Section IV includes the test system and simulation results on multiple (Four) generators and finally the conclusion is being given in section V. References are also given.

II. TRAJECTORY BASED CONTROL

In this section, we basically look the algorithm of Reinforcement Learning. The figure 1 shows the process of damping the oscillations of two generators. In a power system model, The system is running or we can say the power is getting transferred from one place to another using grid. The current state of system is recorded and is feedback to generate an error. An error is generated when the value is not matched with the reference value. The error generated is also known as an action to be taken for improvement is fed as an input to power system stabilizer or controller and the new input is produced. The new input is also known as the reward which when fed to the system as a new input stabilizes the system and system moves to a next state. So here the approach works on four variables namely:

X_t= Current state of system
U= Action taken
R_t= Reward obtained or new input
X_{t+1}= Next state of system

So basically, the system revolves around these four variables or tuples.

We also define a function as:

$X_{t+1} = f (x_t , u_t)$

Above equation is given in [1]

Where the next state of system is a function of current state and action or error or input given to system.

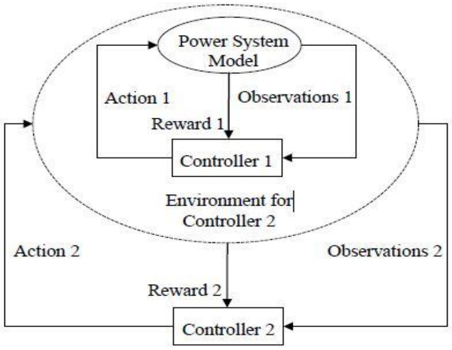

Fig 1: Block Diagram of RL

Diagram taken from [1].The input added to power system stabilizer is then called as reward and made as one of the switch. Actually, there are three switches or we can have number of switches according to our convenience. Let's take for example: We have 4 switches. The one switch is that switch in which error is generated and reward is obtained. The other switch is coming from another stabilizer which handles the rotor speed. The third switch uses no stabilizer or we can say purely zero stabilizer and fourth switch takes the summation of stabilizer input and reference signal. The goal of reinforcement learning is to find the correct switch or correct input which suits the system at that point of time or which stabilize the system. The main work of Reinforcement learning is to find out the exact and correct sequence of input to be fed to the system. The exact here means that system has less number of errors or system is perfectly error-free. Here we are controlling the four parameters namely:

- Sequence voltage V_s
- Rotor Angle Deviation d_Theta
- Rotor Speed W_m
- Output Active power Peo

The control problem is divided into two categories: model based and model free learning. Here we discuss Model predictive control as model based and RL as model free.

III. MODEL PREDICTIVE CONTROL (MPC)

In MPC method,. The model works like as shown in figure2.Here the input is fed to the process and model and error is generated from both their outputs as a corrective action or residual as mentioned in figure. The residual is fed in a prediction block where it is given as an input to control calculation block and again taken as an input to process and model. In this way the system is corrected and controlled.

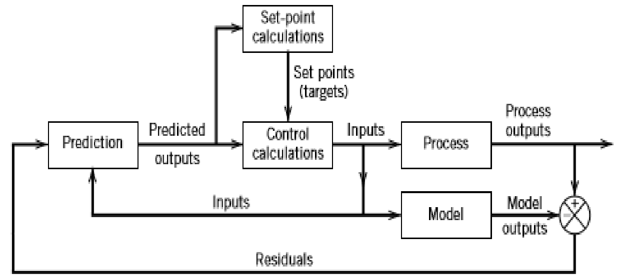

Fig 2: Block Diagram of MPC

Diagram taken from [4].

The simple algorithm is given below in figure3.Here we are talking about three variables namely controlled variable, Manipulated variable, disturbance variable. Through the help of these variables we update model prediction also shown through the block diagram. We determine control structure by doing control calculations and check for ill-conditioning then next step is to calculate set points and perform calculations and send manipulated variable to the process. In this system performance is improved.

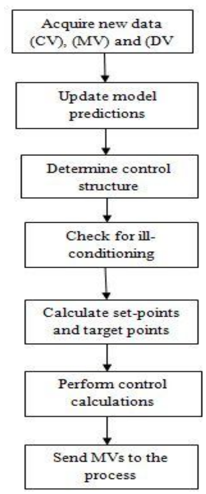

Fig 3: MPC Algorithm

We can predict MPC using model such as step response or difference equation. Transfer function or state space models can also be employed. The advantage of using step response model is that it represents stable process but the major disadvantage is that it requires a large number of parameters.

The step response model can be written as:

$$y(k+1)=y(0)+\sum_{i=1}^{n-1} s(i)\triangleq u(k-i+1)+s(n)u(k-n+1)$$

Above Equation given in [4]

Where y (k+1) is the output variable at (k+1) sampling instant and Δu (k-i+1) denotes change in manipulated input from one instant to next. The model parameters are N step response coefficients. For simplicity y (0) =0.

IV. REINFORCEMENT LEARNING (RL)

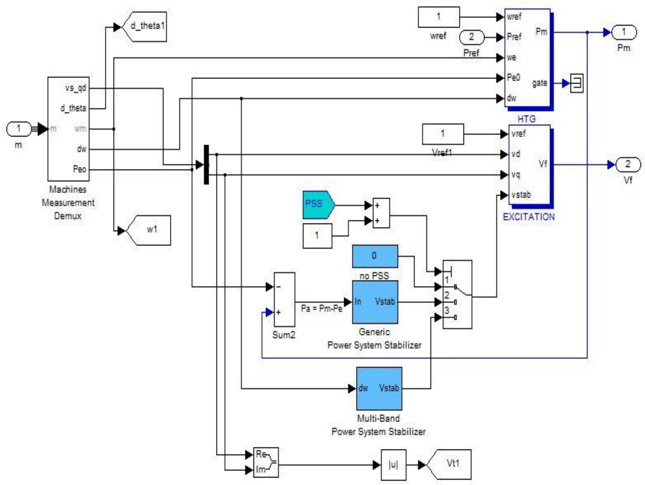

Fig 4: Block Diagram of Sub system

The system consists of the following parts:

- Excitation Block
- Hydraulic turbine governing system(HTG)
- Power system stabilizer
- Multiplexer
- Demultiplexer

The machine measurement Demultiplexer takes a single input and routes it into one of the several output lines. It is also called as data distributor or decoder. The output lines generated from the Demultiplexer are namely: Sequence voltage, Rotor angle, rotor speed and electrical output. The sequence voltage is again Demultiplexer and generate two signals namely quadrature axis voltage and direct axis voltage. These signals are taken as input to the excitation block. Talking about rotor speed, It automatically taken as input to HTG block where mechanical power is generated. The electrical output is sub-divided into two signals where one signal goes to HTG block and other signal goes to the error generator block where subtraction take place and difference is produced. Coming to HTG block, it comprises of five signals namely two reference signals (rotor speed and power). The other three signals have come from the machine measurement Demultiplexer block described previously. The final output obtained from this block is mechanical power abbreviated as P_m. The next important block called to be excitation block comprises of four signals namely reference voltage, direct and quadrature axis voltage and fourth is the stabilizer voltage. The final output obtained from this block is voltage. The stabilizer voltage comes from the switch selected from among four switches. The explanation of function of each switch is explained in section II. In this way, the power system works. Figure 4 only explains the block diagram of one generator or one generating station consisting of one generator. However, for multiple generators multiple block diagrams are used.

V.TREE BASED BATCH MODE RL

In batch mode, we are calculating Q- function based on four variables namely current state, next state, reward and action taken. This approach is searching the best input based on these observations then forming an equation which is basically a Q function which is a function of these four variables. In this way, By analysing the system we can record the values and calculate theses four variables and frame the equations. By doing this, we don't have to frame the equation every time we record the values and by repeating it again and again and studying its results and outputs we can also predict the best state of system. The Q- function is expressed as :

$$Q(s,a) = r(s,a) + \gamma \max_a Q(f(s,a),a_0$$

This is shown by the algorithm given below. Details of tree based batch mode method is given in [2]

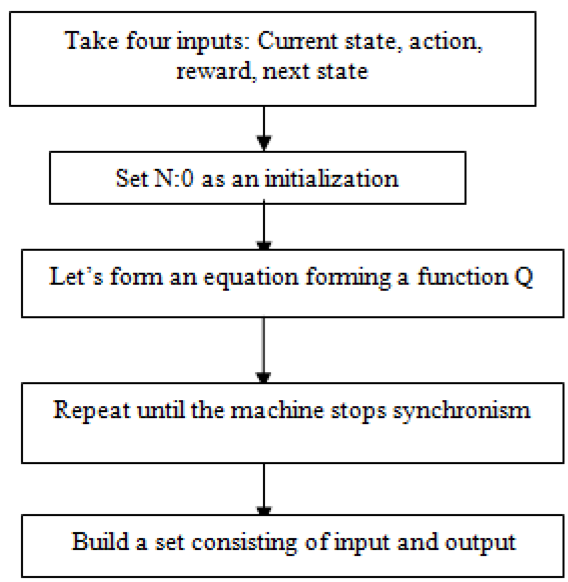

Fig 5: Fitted Q iteration algorithm

VI. TEST SYSTEM AND SIMULATION RESULTS

In this section, the Reinforcement Learning mode is applied on multiple generators (two). Results have been shown with RL and without RL and its impacts on Voltage, power and machine signals. This all have been investigated on a medium size power system model.

A. Test System

The Matlab model of the test system is shown in Fig 6.sThere are four generating stations one of 5000 MVA and other three of 1000 MVA. Four transformers are used to step up the voltage from 13.8kv to 500kv respectively. Fault type A occurs at line of length 350km leads to oscillations. The following information is represented in tabular form:

Table 1: Fault Data

Three phase fault resistance is	.001 ohm
Ground resistance	.001 ohm
transition state	[1, 0]
transition time	[0.1, 0.2]
Snubber resistance	1Meghaohm
Fault duration	0.1 second

Three voltage-current measurements are used namely B1, B2, B3 respectively. A switch is there to select the operation of PSS. RL is inbuilt in Power system stabilizer. Four generating stations feeds three loads of 1000,1000 and 5000 MVA. The voltage and power is shown in PV measurement block. Various machine parameters are shown namely theta, voltage and power. We see that system when controlled without RL exhibits poorly damped oscillations and when controlled with RL exhibits damped oscillations.

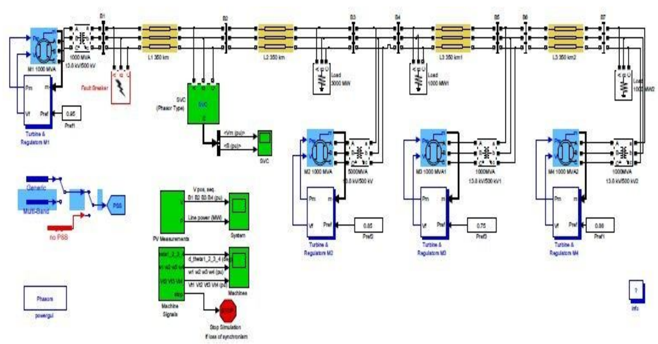

Fig 6: Test system

B. RL- Based control of multiple generators

Design of RL controllers on four generators should be carefully approached because when RL acts alone does not imply good results. If we are applying RL on more than one generator then we should learn each stabilizers properties. The generator current states are recorded action taken and rewards obtained are solved. This process is repeated till we get four samples of Q-function. As we know the generator runs through a turbine regulator set. When we analyze our test system , the HTG (Hydraulic turbine set consists of Power system stabilizer. According to RL , Firstly to collect four samples, various trajectories under a series of various inputs are simulated. Disturbance occurs for 0.1 second. So after every 0.1 second the current states are sampled and then inputs are applied. The next state is reached and we obtain one step reward. Q function is calculated on iteration. The steps are same as follows. Firstly the current state is recorded then action or input is applied from an action space and when next state is reached and reward is obtained we get our Q function by searching based on Tree based batch mode reinforcement learning [2]. The input with the largest Q function is being selected as an input to the existing PSS. But this method is self learning approach and system adapts itself through adaptive learning. According to our test system, Type A fault of three phase is generated within a line after every 0.1 second and error is feedback to Stabilizer or controller to improve the damping.

The system when not controlled through RL exhibits poorly damped oscillations as shown. Figure 7 shows the power of four machines. Figure 8 shows the Line voltages without RL and figure 9 shows the maximum voltage of four machines without RL. Figure 10 shows the sequence voltages line power and sequence voltages of two machines without RL. Figure 11 shows line power and finally Figure 12 shows the angle deviation without RL. So we can clearly see from the graphs that machine has so many oscillations which lead to threat to system and sometimes lead to system failure also. Previous study and analysis is given in [10].

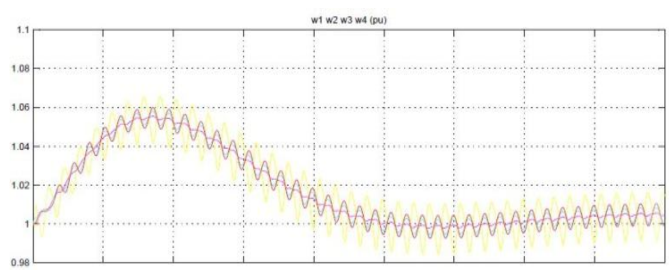

Fig 7: W1,W2,W3 & W4 of the system when controlled without RL

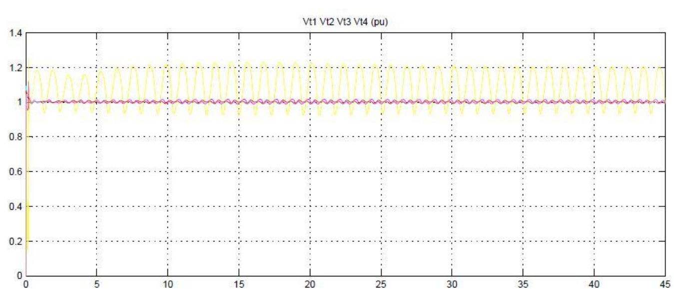

Fig 8: Line Voltages Vt1, Vt2, Vt3 & Vt4 without RL

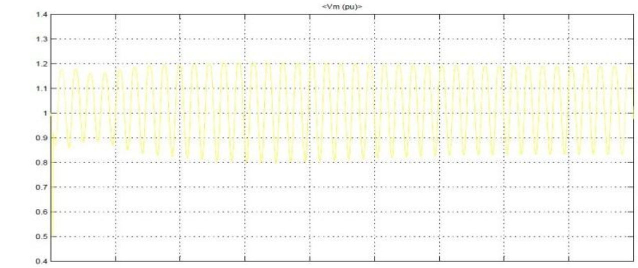

Fig 9: Maximum Voltage Vm (Pu)

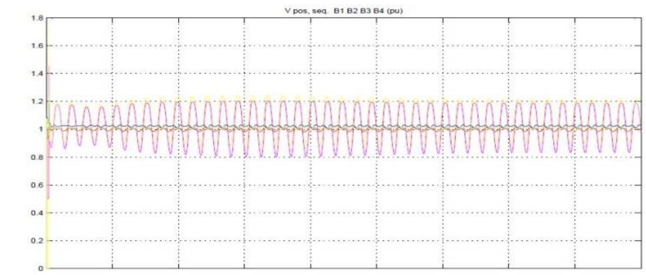

Fig 10: Sequence Voltages Without RL

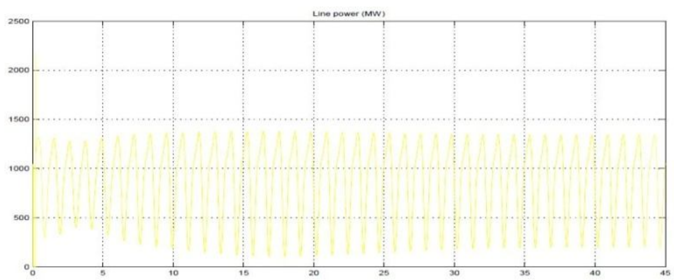

Fig 11: Line power without RL

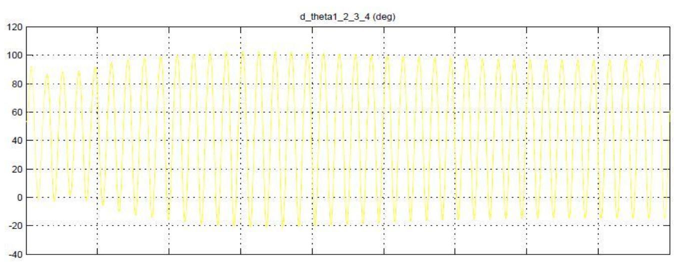

Fig 12: theta without RL

After applying RL inbuilt on power system stabilizer. We get the following waveforms. Basically we are choosing the controller through a switch (Single Pole double throw switch)

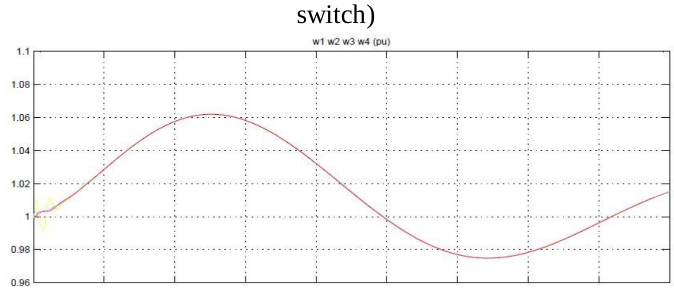

Fig 13: W1, W2, W3 & W4 of the system when controlled with RL

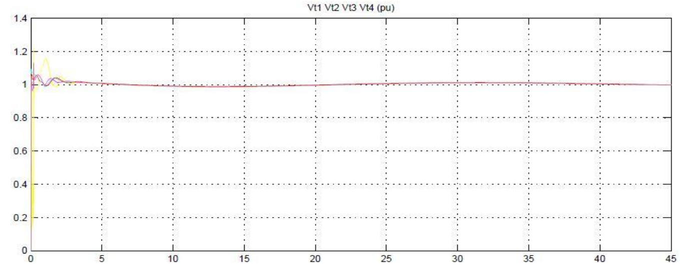

Fig 14: Line Voltages Vt1, Vt2, Vt3 & Vt4 with RL

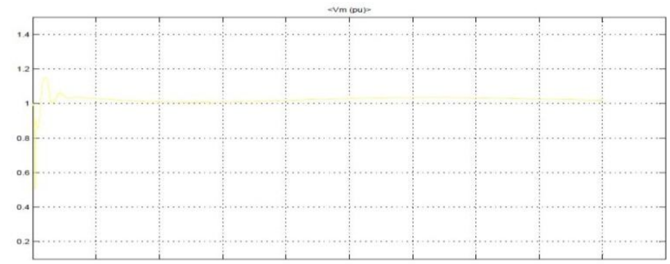

Fig 9: Maximum Voltage Vm (Pu)

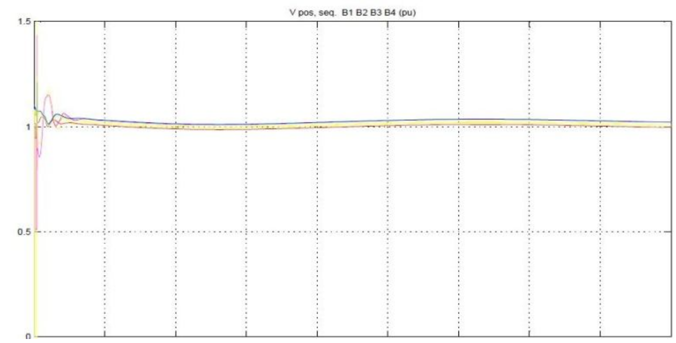

Fig 15: Sequence Voltages With RL

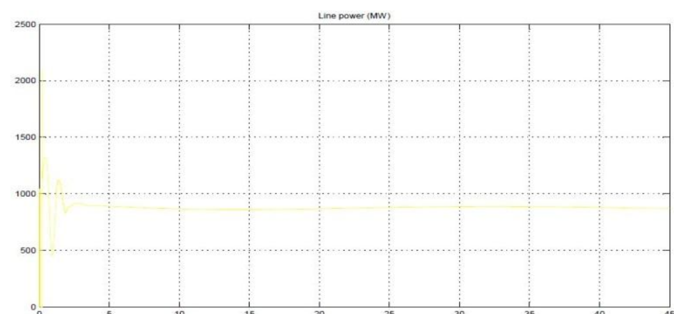

Fig 16: Line power

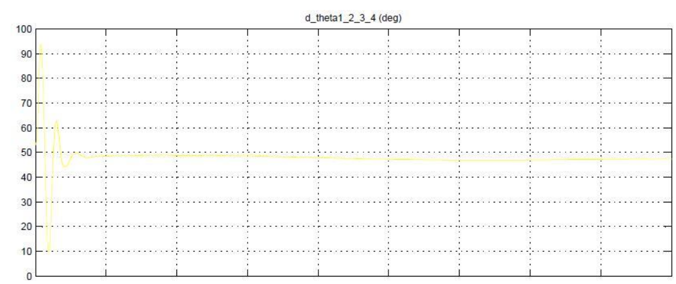

Fig 17: theta with RL

Figure 12,13,14 shows the power, line voltage and maximum voltage of genarators with RL mode. Though it brings oscillations in first few seconds but later on, damping effects are quite good. Figure 15 shows the sequence voltages of machine with RL.Figure 16 shows the line power with RL. Figure 17 shows the angle deviation theta with RL mode. We can see the damping effects are very much improved. In four samples obtained the rewards obtained not only depends on inputs applied but also the input of other generator.

VII. CONCLUSION

This paper represents the trajectory based approach for the damping of electromechanical oscillations. It uses four generators. It is not in anyway to replace the existing methods rather it superimpose the inputs on the outputs of controllers. This paper basically solves Q function based on four samples.This method improves the damping effects of existing controllers. Before dealing with multiple generators, we should learn each generator control policy and properties. This method can also be combined with MPC as shown in [1].however we have focused only on RL. We have examined various machine parameters namely theta, line voltage using RL approach. One main advantage of this approach is that it is a self learning approach and system adapts automatically after computing the four samples. However finding four tuples is a bit challenging task. One problem we suffer from is that it needs computational resources to build. We have used only four machines but we can control multiple generators using this approach. Though it needs a large number of computational sources but still it is very easy as compared to model based approach. This approach can be used at high level of power system as well.

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REFERENCES

[1] Da .Wang, Trajectory based supplementary damping control, in IEEE 2014

[2] D.Ernst"Tree based batch mode reinforcement learning" Journal of machine learning research Vol 6 2005

[3] Csaba Szepesv, Algorithm of reinforcement learning June 2009

[4] R.R. Negenborn, B. De Schutter, M.A. Wiering, and H. Hellendoorn, Learning-based model predictive control for Markov decision processes, july 2005 Delft University of technology

[5] Nahum Shimkin, lecture notes on reinforcement learning a basic algorithm 2011

[6] Damping controller design for power system Oscillations, Rusejla Sadikovic

[7] 2006 damping controller design for FACTS devices in power systems using novel control techniques, Qian Liu, Iowa State University

[8] G.Rogers, Power System Oscillations,Kluwer Academic Publishers,2000

[9] R.Sutton and A. Barto ,Reinforcement Learning: an Introduction MIT Press,1998