Trajectory Based Damping of Electromechanical Oscillation

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Abstract-*This paper represents an implementation of trajectory based damping of electromechanical oscillations. We basically use Reinforcement Learning (RL) to improve damping by generating supplementary inputs to be applied to the generator. This paper also compares the Model Predictive Control (MPC) and RL .The RL based control scheme is first implemented on single generator and several possibilities have been investigated to extend it to Generators.*

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

I. INTRODUCTION

The power system oscillations are observed when the synchronous generators are interconnected to provide more power. The electromechanical oscillations are divided into two categories:

Local Modes: oscillations associated with a single generator or a single power plant. These oscillations have the frequencies in the range 0.7 to 2Hz.

Inter-area modes: the generators in one sub-area oscillate against the generators in other sub-areas. Inter-area oscillations have their frequencies in the range 0.1 to 0.8Hz. Once excited, inter-area oscillations may propagate over the whole system.

Our focus is on inter-area oscillations. Oscillations are acceptable if they last for few seconds or decay rapidly. Increasing oscillations lead to tripping, failure of system and even blackouts. Diverse controllers and actuators are placed in power systems initially for certain reasons other than to damp oscillations. Once installed, these devices also can be used to increase the damping of certain electromechanical oscillation modes. Power system stabilizer use local measurements at their inputs. The parameters usually remain fixed in practice. It is cost affective. The FACTS devices like Statcom, Thyristor controlled series capacitor control node voltages, change line impedances and adjust power flow. HVDC modulation is also used to damp AC oscillations.

Typical model based design of damping controllers begins with the recognition of oscillation modes, determining the controller parameters which is also calculated based on local information and remains fixed and ends with time domain simulations.

The rest of the paper is organized as follows: Section II describes the trajectory based approach by model based and model free learning method. Section III describes the tree based batch mode RL method. Section IV includes the test system and simulation results and finally the conclusion is being given in section V. References are also given just to add up the knowledge.

II. TRAJECTORY BASED CONTROL

In this section, the trajectory based damping control is introduced by model based and model free learning methods.

The principle of model Predictive control method is: It uses collected measurements, model of system and its specifications. The computed optimal controls are applied to the system. As soon as updates are available entire procedure is repeated. Basic idea of MPC is to define a set point trajectory so that real output should follow. A set point trajectory is an ideal or reference trajectory. At time K, controller collects current states and calculates trajectory using the model in order to obtain the best possible future behavior wrt reference. Once future trajectory is chosen, only the first element of trajectory is applied as real input.

The power system is considered as discrete time process. The trajectory is given in the form as derived from the model:

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

Where Xt is a state vector and ut is an input vector. Using certain inputs/control signals, we can force the system to travel desired trajectory to improve damping. The goal of this method is to find out the correct and exact sequence of inputs (up0, up1,up2………..). That means the system has not large errors and it travels along the desired trajectory. When the system states move from xt to xt+1, after applying action/input ut, a reward rt is obtained. As discussed, the input is regarded as the difference between the rated synchronous speed of rotor and the actual speed of rotor which is defined as :

$R_t = \int (p_g - p_{ref})\, dt$

We start from state xt and apply an input or action ut we get a reward or return(for long process) rt. Starting from an initial state xt and after applying sequence of actions or inputs, we get a sequence of rewards rt. so the discounted return R over a region of t is given as :

$R = \sum_{i=0}^{t-1} y r_{t+i}$

Where y is a discounted return and rt+I is a successor state of reward. Details of this system are given in [1].

Model based and Model –free solution methods

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.

Model predictive control (MPC):

In MPC method, the output variables are known as controlled variable while input variables are known as manipulated variable. The process model finds the dynamic and static interactions between input, output and disturbance variables. The MPC calculations are based on current measurements and predictions of future value of outputs. MPC works as follows: at a control time, based on current measurements, calculate a sequence of inputs minimizing/maximizing the function.

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.

Reinforcement Learning (RL):

For understanding Reinforcement Learning, we have to understand the concept of agent. An intelligent agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators in order to reach a certain goal. The human is a good example of intelligent agent. A human agent has eyes, ears and other organs for sensors and hands, legs, mouth and other body parts for actuators.

III. TREE BASED BATCH MODE RL

In batch mode, we calculate Q function which is based on four variables namely (xt , ut , rt , xt+1). Xt denotes the system state at time t, ut denotes the control action taken or input, rt is the instantaneous reward obtained and xt+1 is the next state of the system. When the action or input and state are finite enough, the Q function can be represented in table form but when we deal with discrete or continuous system then Q function must be represented in the form of four variables.

The fitted Q iteration algorithm is a batch mode which finds an approximate value of Q function corresponding to an infinite horizon.

At first iteration it produces an approximate value of Q1 function. Since the true function is the conditional expectation of reward given by state action pair. A training set consists of inputs (xt, ut) and outputs rt.

The N-iteration also uses a batch mode algorithm, which provides an approximate value of Q function corresponding to N-step. The training set is obtained by previous step by merely iteration. This is shown by this algorithm. Algorithm and details of tree based batch mode method is given in [2]

To build a tree:

We have to build a tree from the training set consisting of inputs and actions. To determine the splitting of node we select K cut directions at random. For each K cut direction we choose the one that maximizes the score. The state action pairs related to node are split into left or right subset. Then these subsets again build a tree. Then we create a node with these subsets are we get a tree. Here we apply actions (-.015,.015). The inputs and outputs expressed as:

$i = (x_t, ut)$
$o = r_t + ymaxQ_{n-1}(x_{t+1}, u)$

IV. TEST SYSTEM AND SIMULATION RESULTS

The diagram is shown in figure 1. The power system toolbox is used to simulate the response. The power system stabilizer is installed in each system. The system is made of two areas A1 and A2 connected through tie lines. A temporary three phase short circuit fault is also generated which lead to oscillations. When controlled through PSS, system exhibits poorly damped oscillations. The two area system is connected through TCSC which is shown in Fgure3.The area A1 is given consisting of 8 generators combining both areas we get 16 generators in total.

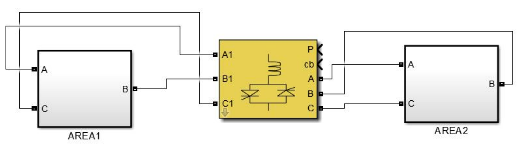

Figure 1: Test system

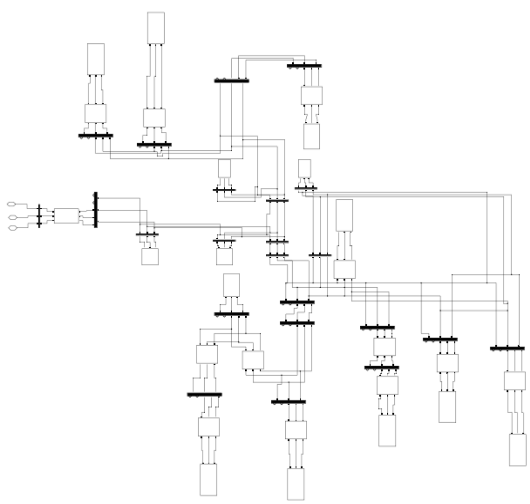

Figure 2: Area 1 of the system

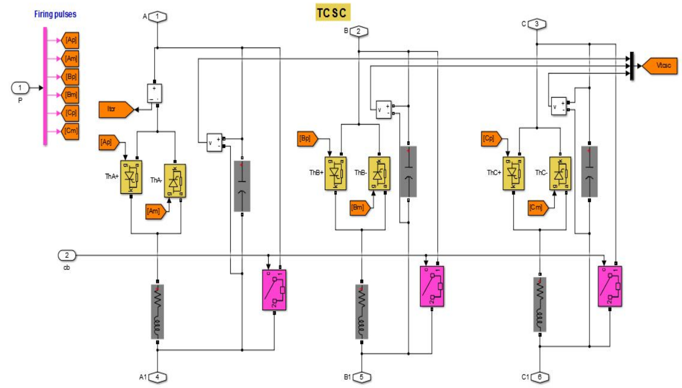

Figure 3: TCSC

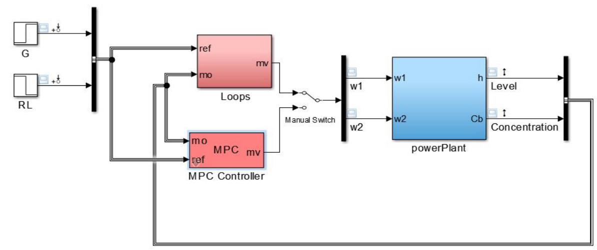

Figure 4: Combination of RL and MPC

RL based control of single generator:

We have to collect four samples by simulating 500 system trajectories under fault durations ranging from .01 to .05 seconds. Every .1 second after disturbance, current states are sampled and action from (-.015, .015) are applied. The candidate action space includes all the inputs. St+1 reached and reward obtained.

$$r_t = -\int_t^{t+1} w - wref$$

All in all 2500simulations are run and 200000 tuples are obtained. Based on four tuples, extra tree is built.

Q function based greedy decision making

Collect the current states and select an action. Calculate a Q-value by searching 100 trees and averaging their output. All candidate action space is probed and action with largest Q value is selected as an input to Power system stabilizer.

RL based control of multiple generators

To ensure the design of multiple controllers, approaches have been adopted:
Learning each controller in absence of other controllers.

Separate sequential learning of the controllers (agents): a sequence of random actions to a first generator is first applied in order to yield its training sample while using the current control strategy for all other generators. Figure 5 represents the active power in line with RL , with MPC and both combined. Fig.6 displays system response (solid lines) when the tree based batch mode RL is applied only on generator 1. We observe that the introduction of this single supplementary control already improves the damping. The use of different generators would produce different contributions to oscillations damping. Figure 7 display the power of generators.

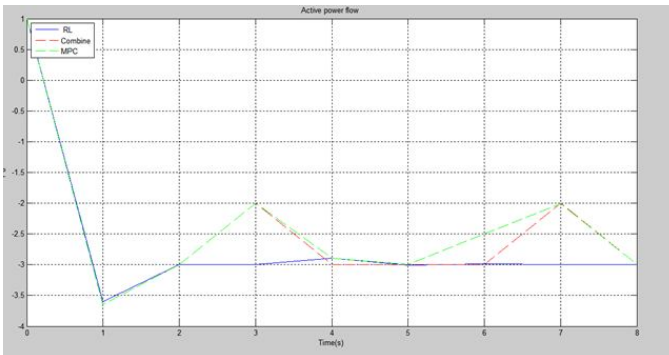

Figure 5: Active Power Flow of line

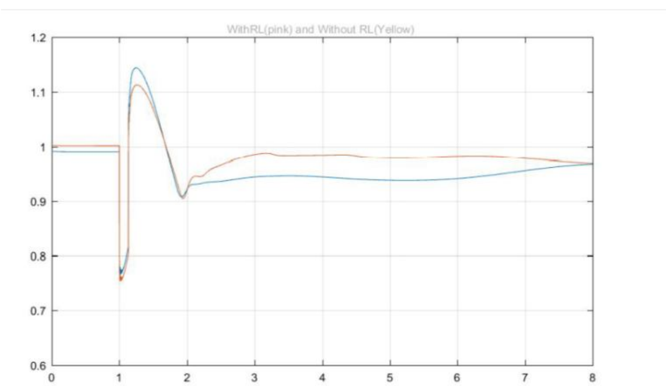

Figure 6: Angular speed of generator

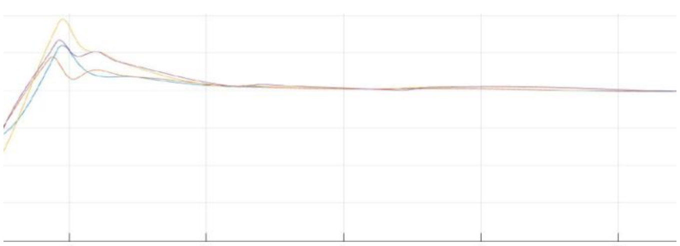

Figure 7: Power of generators

V. CONCLUSION

This paper represents the trajectory based approach for the damping of electromechanical oscillations. It does not intend to replace the existing methods but to superimpose the inputs on the outputs of controllers. Here the problem is treated as a discrete set of equation.

This paper basically approximates Q function based on four samples. It uses a tree based batch mode method. This method improves the damping effects of existing controllers. Before dealing with multiple generators, we should learn each generator control policy. This method can also be combined with MPC as shown in [1].however we have focused only on RL. 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. 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 and also at a very local level.

ACKNOWLEDGMENT

I am greatly indebted forever to my guide Prof. K.V. Rammohan Asst. Prof. Department of Electrical Engineering. for his continuous support, ideas, most constructive suggestions, valuable advice and confidence in me. I express my gratitude and sincere thanks to Prof. Ms. AlfiyaA.Mahat, Head, Department of Electrical Engineering for his constant motivation and support. I sincerely thank Dr. S.K.Biradar, Principal, MSS'S College of Engineering and Technology, Jalna for his continuous encouragement.

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