Hybrid Energy Function based Real-Time Optimal Wide-Area Transient Stability Controller For Power System Stability

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***Abstract*—This paper presents a hybrid direct and intelligent method of real-time coordinated wide-area controller for improved power system transient stability. The algorithm is applied as an optimal Wide-Area System-Centric Controller and Observer (WASCCO) based on Adaptive Critic Design (ACD). ACD techniques that uses Reinforcement Learning (RL) could be utilized to approximate the transient energy function by dynamic programming and find the solution to nonlinear optimal control problem. However, such technique yet is highly dependent on the cost function and its dynamics. A Lyupanov-based energy function that is defined offline and updated in real-time through Prony analysis is utilized for this purpose. Results on a two area power system and 68-bus New England New York system shows better response compared to conventional schemes and local power system stabilizers.**

***Keywords*—Adaptive Critic Design, Artificial Intelligence, Real-time Simulation, Transient Stability, Wide-Area Control.**

I. INTRODUCTION

MODERN power systems are considered more complex and nonlinear than before due to significant integration of distributed energy resources, severe transmission congestion and growth of energy markets deregulation. This extreme nonlinearity of modern power system makes the classical stability classifiers and controllers non-practical, yet applicable for small signal stability analysis [1]. Thus, for transient stability analysis and control of interconnected wide-area systems, designing global optimal dynamic damping controllers capable of tracking nonlinear dynamics of system is necessary. Wide-Area Control System (WACS) coordinate the actions of a number of distributed agents using supervisory control by means of Wide-Area Monitoring (WAM) information.

Various approaches to wide-area real time transient stability assessment and control have been proposed in the power systems literature [2]–[6]. Classical techniques such as numerical integration and direct methods were utilized in early years, each having their own advantages and disadvantages. For example, numerical methods have shown considerably weak performance in real-time implementation, especially, wide-area application, as it requires accurate information of the power network topology [7]. Direct methods analyze transient stability using direct calculation of the Transient Energy Function (TEF). Thus, such problem formulation may lead to excessive simplifications. With the advent of technology new techniques and approaches based on combination of these methods have been developed. These approaches mainly rely on equivalent modeling which can actually be integrated much faster than real-time. Further, direct energy methods can be utilized to predict the transient stability status of the system, as well as, the stability margins [8]. Another hybrid method to tackle the problem is early-termination criteria, allowing simulation of stable cases to be aborted as soon as possible [9]. This criteria for numerical simulations can be defined on the basis of coherency, transient energy conversion between kinetic energy and potential energy, and the product of system variables [10].

Artificial intelligence techniques on the other hand, have shown the capability of dealing with such nonlinearities and uncertainties, in a more reliable and stable way [11]. Intelligent-based techniques have shown great potential in wide-area stability classification and control due to their speed in Transient Stability Analysis (TSA) [12]. Various advanced artificial intelligent techniques as well as machine learning and data mining approaches have been tried to develop TSA and promising results have been obtained. These methods effectively learn and map the process behavior from relationship between specified inputs and outputs, without any prior knowledge of the system. Decision Tree algorithms [13], Fuzzy Logic techniques [10], Neural Networks (NNs), and Support Vector Machines (SVMs) [13] has been widely used as a benchmark for transient stability prediction, classification, and control. These actions are performed online, through matching the online monitored data with some offline expert knowledge. This new knowledge can inturn improve the training for further events or recursively at each iteration, such as in the case of Reinforcement Learning (RL) algorithms [14]–[16]. However, most of the works in this area has been designed as classification and remedial actions schemes rather than real-time damping control schemes. R. Hadidi et al in [14] proposed real-time decentralized wide-area control scheme based on Q-Learning for excitation control of generators. In [16], new concept called a virtual generator for wide-area monitoring and control has been introduced, in which RL is performed for wide-area damping. One of the main challenges of such designs is the need to have an optimal cost function that can define the transient stability problem accurately.

In Adaptive Critic Designs (ACDs), one of the common techniques of RL implementation, critic NN performs cost function estimation based on incremental utility function U or in Lyapunov sense $\dot{V}$. With Lyapunov stability criteria, positive V and negative $\dot{V}$ satisfies the stability convergence, yet, may not be an optimized solution. In conventional methods, usually, utility function considered in ACD defined by the Euclidean norm of the desired states may not be a full representative of the goal of transient stability condition as well. In addition, methods for solving the above problem based on energy estimation of generators, may not be practical in real life. Thus, in this paper, a method that can overcome this problem by linking the cost function to Lyupanov energy function through eigenvalue analysis in offline mode is proposed. The main advantage of this method is that it can be performed in real-time as well, by monitoring the system modes online and tuning the utility function iteratively. The method is evolved from [17] for real-time wide-area monitoring and control of large power system. Benefits of this method over conventional methods can be highlighted in multi-area systems, monitoring and controlling inter-area oscillation modes, in a form of tuneable cost function rather than static one based on local states.

As a machine learning method, offline training should be performed before taking any actions in real-time. For this, an Input/Output (I/O) specification based on the proposed method is set initially. These input specification can be states derived from Phasor Measurement Unit (PMU) needed to estimate the energy function. Then, an offline training is performed based on the I/O signals. This action is performed by training the NNs of ACD with pseudo random inputs in the batch mode. The control action is chosen based on cost function optimization. The proposed method links stability criteria with optimality conditions using offline and online eigenvalue estimation. In online process corresponding iterative procedure changes the utility function by updating the coefficient matrix of system states. Simulation results shows that the inter-area and local oscillation can be better recognized and controlled through this online tuning.

The paper is organized as follows. The second section provides a brief overview of system modeling and direct energy function development. In section III, the proposed Wide-Area System-Centric Controller and Observer (WASCCO) design is illustrated and Section IV discusses the proposed offline and online cost function tuning methodology. Section V presents the implementation test bed evolved from [18] and test results followed by future works and challenges in real-time simulation and conclusions in section VI and VII respectively.

II. System Modeling and Direct Energy Function Development

The problem of direct transient stability of power systems is usually assessed by using a simplified synchronous generator model. In this paper, the third-order generator model is used as,

$$\dot{\delta} = \Delta\omega \tag{1}$$

$$M\Delta\dot{\omega} = P_m - P_e - D\dot{\delta} \tag{2}$$

$$T'_{do}\dot{E}'_q = (E_f - \hat{E}_f) - (E_q - \hat{E}_q) \tag{3}$$

where, δ is the rotor angle, $\Delta\omega = \omega - \omega_s$ the speed deviation, M the inertia constant of the synchronous generator, P_m the mechanical power, P_e the electrical power, D damping coefficient, E_q the quadrature-axis component of internal voltage, E'_q quadrature-axis component of transient emf, T'_{do} the open-circuit transient time constant,and E_f is the excitation voltage. The symbol "hat" denotes the static operating point.

An energy-type Lyapunov function for such a system model (V) comprises of the sum of the system kinetic energy (V_K) and potential energy (V_P) with respect to the equilibrium point. For the third-order generator model a Lyapunov function of a component proportional to the squared deviation of the transient emf, so-called field energy (V_F) is also included [19]. Therefore,

$$\begin{aligned} V &= V_K + V_P + V_F \\ &= \frac{1}{2}M\Delta\omega^2 - \int_{\Delta\delta}^{\Delta\delta}[P_m - P_e]d\delta \\ &+ \frac{1}{2}\frac{\alpha}{\beta}(E'_q - \hat{E}'_q)^2 \end{aligned} \tag{4}$$

$$\begin{aligned} \dot{V} &= -D\Delta\omega^2 - \frac{1}{T'_{d0}}\frac{1}{\Delta X_d}(E_q - \hat{E}_q)^2 \\ &- \frac{1}{T'_{d0}}\frac{1}{\Delta X_d}(E_q - \hat{E}_q)(E_f - \hat{E}_f) \end{aligned} \tag{5}$$

where, α and β are parametric coefficient based on synchronous and transient reactances and the transfer admitance matrix, $\Delta X_d = (X_d - X'_d)$ with X_d and X'_d as synchronous and transient reactances, respectively.

With the assumption of $\hat{E}_f = \hat{E}_q$, and $(E_f - \hat{E}_f) = K(E_q - \hat{E}_q)$, where the gain $K > 0$, we get,

$$\dot{V} = -D\Delta\omega^2 - \frac{1}{T'_{d0}}\frac{1+K}{\Delta X_d}\Delta E_q^2 \tag{6}$$

and, by denoting the second coefficiant as D',

$$\dot{V} = -D\Delta\omega^2 - D'\Delta E_q^2. \tag{7}$$

III. Intelligent System Construction

ACDs are, in general, parametric structures capable of optimization over time and under conditions of noise and uncertainty [11]. The goal of ACD is to learn the Hamilton-Jacobi-Bellman equation associated with optimal control theory through critic network, and find the control signal through Action network [11]. Training of Action network is based on selecting sequence of actions that minimize the estimated cost function (J). Machine learning technique is used as a tool for mapping from a parameter space into the space of functions they aim to represent. A common approach is to deploy NN to map the nonlinearities of the system identification, control and the cost function. In this paper, using Feed Forward Neural Network (FFNN) the network output is computed by inner product between the weight vector W and a state-dependent feature vector $\Phi(.)$. The Wide-Area NN Identifier (WANNID), Critic NN, and Action NN, approximate the dynamics of the system, the control action, and the cost function, respectively by,

$$x(t+1) = W_I(t)^T\Phi_I(x(t), u(t)) + B_I(t) \tag{8}$$

$$u(t) = W_A(t)^T\Phi_A(x(t)) + B_A(t) \tag{9}$$

$$J(t) = W_C(t)^T\Phi_C(x(t)) + B_C(t) \tag{10}$$

where, sub-scripts I, A, and C denotes WANNID, Action, and Critic networks respectively. $\Phi(.) \in \Re^j$ is the corresponding nonlinear mapping function of the states, $\hat{W}(t) \in \Re^j$ is the parameter vector of approximated weights of the FFNN at time t, with $j \in \mathbb{N}$ dimensionality of the feature vector representing each state, and B is the bias coefficients. This optimization is done by means of training the NNs through gradient descent via back-propagation.

A. *Cost function and Transient Energy function*

Based on RL approach, it is desired to find the control action which minimizes the cost-to-go function given as

$$J(t) = \sum_{k=0}^{\infty} \gamma^k U(t+k) \tag{11}$$

Where, $\gamma \in (0, 1]$ is the discount factor, and U is the utility function used for reward/punishment in terms of RL concept, or incremental cost function in Lyapunov stability concept. This function can be represented as,

$$U(t) = -\Delta x(t)^T Q \Delta x(t) - u(t)^T R u(t) \tag{12}$$

where, the weighting matrix Q is required to be positive-definite, and $\Delta x(t) = x(t) - \hat{x}$. In this paper, R as a weighing coefficient of control action are considered constant.

In the sense of Lyapunov stability criteria, this cost function should be always positive. This criteria can be analyzed at each time step, by checking the estimated cost function by means of critic NN. If the cost function is named as $V(x)$, a Lyapunov function candidate, then it can be proved that the system is asymptotically stable in the sense of Lyapunov stability criteria (Proof left due to space limitation).

$$J(t) = V(x(t)) \geq 0 \tag{13}$$

In the sense of Lyapunov stability criteria ? is always true

$$U(t) = \dot{V}(x(t)) = \frac{d}{dt} V(x(t)) \leq 0 \tag{14}$$

B. *Adaptive Critic Design Training*

As a machine learning methods, offline training should be performed before taking any actions in real-time. In addition, as a RL technique online training is the main feature adapting to optimal solution, yet weighing up the importance of training. The technique used in this paper is a simple Heuristic Dynamic Programming (HDP) for implementation and training the ACD.

The process of training a NN requires computing an error value that describes how the NNs output varies from the target value. Back-propagation algorithm being adapted to wide use in training NNs, allows us to calculate the sensitivity of each component of the NN to the error and minimize it [11]. As mentioned before, there are three NNs that have been implemented in WASCCO: WANNID, critic network, and action network. In particular, the training process of the critic NN is based on dynamic programming, which, estimates J^* by updating its policy with respect to error, e_C, with elements of the rewards obtained from the environment, $U(t)$, which will be discussed in next section, the cost functions at current time step, $J(x(t))$, and future time step, $J(x(t+1))$, estimated by (10). This can be written as,

$$e_C(t) = J(x(t)) - \gamma J(x(t+1)) - U(x(t), u(t)) \tag{15}$$

where, critic NN future outputs is based on predicted states derived from WANNID. Training of the identification NN is derived as,

$$e_I(t) = x(t) - W_I^T \Phi_I(x(t)) \tag{16}$$

and, the action training is based on minimizing the derivative of cost function to action chosen. The purpose is to have the action error asymptotically goes to zero in an iterative process. This can be derived as,

$$e_A(t) = \frac{\partial U(x(t), u(t))}{\partial u(t)} + \frac{\partial J(x(t+1))}{\partial x(t+1)} . \frac{\partial x(t+1)}{\partial u(t)} \tag{17}$$

where, the elements of this error value can be calculated by means of back propagation through Critic NN and WANNID with the equations of (10) and (8) respectively.

Change of each NN weights at time t can be derived from the deviation of NN's output to its optimal value, $e(t)$ by means of gradient descent via back-propagation through the NN model. This can be written as,

$$\dot{W}_t = \alpha e(t) \Phi(x(t)) \tag{18}$$

where, α is small step size learning parameter.

IV. Transient Stability Cost function approximation

The concept of transient stability cost function optimization is highly dependent on the utility function. First, the RL problem should be design to address the transient stability criteria. This matter is done by setting the utility function as derivative of Lyupanov stability function. The coefficients of this function are accessible offline and through small signal stability analysis. Further more, online tuning of utility function is critical, especially in the case of dealing with transient stability analysis. So far there has not been many methods that uses such tuning. This section discusses a novel method for tuning the utility function based on the system response and feedback. Here, the goal is to address the inter-area and local oscillation of transient stability analysis in the optimization cost function of ACD.

A. *Offline Energy Function Estimation*

As mentioned in previous section, cost function is estimated based on utility function, which is defined on states and Q as the weights of the states (12). As presented in (7), states needed to monitor the transient energy deviation are $\Delta\omega$ and ΔE_q. In the offline simulation the coefficients could be estimated and calculated by eigenvalue analysis of small signal stability. As,

$$D_i = 2M_i \omega_{ni} / \zeta_i \tag{19}$$

where, $\lambda_i = -\zeta_i \omega_{ni} \pm \omega_{ni} \sqrt{\zeta_i^2 - 1}$ is the eigenvalue related to oscillatory mode i of the system, ζ is the damping ratio, and w_n is the natural frequency. In order to develop the D matrix, participation of each generator on that mode is considered, as,

$$D = \sum_i 2M.pf.\omega_{ni} / \zeta_i \tag{20}$$

where, $M = [M_1, .., M_n]$ is the vector of the inertia of generators and pf is the vector showing the participation of each generator, actually state of ω of the generators, in that specific mode of oscillation. Coefficient of D' is also defined as,

$$D' = (1 + K)/(T'_{do}\Delta X_d) \tag{21}$$

For the MIMO power system, with $\Omega = [\omega_1, .., \omega_n]$, and $E_Q = [E_{q1}, .., E_{qn}]$, then

$$U(t) = -\begin{bmatrix}\Delta\Omega(t)\\ \Delta E_Q(t)\end{bmatrix}\begin{bmatrix}D & 0\\ 0 & D'\end{bmatrix}[\Delta\Omega(t) \quad \Delta E_Q(t)] \tag{22}$$

where, D and D' monitor the inter-area oscillations of the states as well as local ones.

B. Online Energy Function Tuning

In the online energy function or utility function estimation, eigenvalues are determined online and the goal is to relate the desired eigenvalues and performance criteria by finding Q that corresponds to a set of preferred eigenvalues. In general, there is no unique solution to this problem as construction of Lyapunov function only demands V being positive and $\dot{V}$ being negative. Here, the Q matrix is determined so that the closed-loop system obtains a set of preferable eigenvalues. Thus, there is a need to monitor and analyze the eigenvalues of the state matrix and identify power system oscillation modes.

Prony method is used, to determine the unknown eigenvalues of the system [20], [21]. This method is based on a measured states, $x(k)$, being represented in discrete time as a sum of n damped complex sinusoids [20].

$$x_k = \sum_{i=1}^{n} \bar{R}_i Z_i^k \tag{23}$$

$$Z^n + a_1 Z^{n-1} + a_2 Z^{n-2} + ... + a_n = 0 \tag{24}$$

where R_i is an output residue corresponding to the mode λ_i. The vector $A = [a_1, .., a_n]$ leads to the eigenvalues, Z_is, of the system which are the roots of the system characteristic equation. Once the roots of the system characteristic equation are obtained, the eigenvalues with high frequencies, that are known not to be present in power systems, are neglected. This analysis leads to obtaining the eigenvalues of the system in order to detect inter-area oscillation and local ones, which later is used to adapt the weighing matrix of the states accordingly.

Further, in the proposed approach, desired eigenvalues and performance criteria are related through Riccati equation to detect and damp inter-area oscillations as,

$$\begin{bmatrix}\dot{x}\\ \dot{\rho}\end{bmatrix} = \begin{bmatrix}A & -BR^{-1}B^T\\ -Q & A\end{bmatrix}\begin{bmatrix}x\\ \rho\end{bmatrix} = F\begin{bmatrix}x\\ \rho\end{bmatrix} \tag{25}$$

where A, B, and K are available through state identification as $\dot{x} = (A + BK)x$ with backpropagation through identification and action NN blocks. From (20), it can be noted that, the eigenvalues of the closed loop system are identical to those eigenvalues of the F that have negative real parts. Therefore, instead of the eigenvalues of the feedback system, eigenvalues of F matrix can be used for further analysis. This allows us to generate eigenvalues linking to the weighting matrix Q in the performance criterion without solving the Riccati equation. We determine a unique Q which gives the feedback system a set of preferable eigenvalues when its shifted towards unstable region in presence of faults. The proposed decoupling method can be used to obtain M and λ matrix from states developed by Prony method. This also transforms the cost function J, corresponding matrix Q, and Riccati equation to diagonal form as follows

$$z = M^{-1}x \tag{26}$$

$$J = \frac{1}{2}\int_0^\infty [z^T\tilde{Q}z + a^T Ra]dt \tag{27}$$

$$\tilde{Q} = M^T Q M \tag{28}$$

$$\begin{bmatrix}\dot{z}\\ \dot{\tilde{\rho}}\end{bmatrix} = \begin{bmatrix}\Lambda & -H\\ -\tilde{Q} & \Lambda\end{bmatrix}\begin{bmatrix}z\\ \tilde{\rho}\end{bmatrix} = \tilde{F}\begin{bmatrix}z\\ \tilde{\rho}\end{bmatrix} \tag{29}$$

where,

$$H = M^{-1}BR^{-1}B^T M^{-T} \tag{30}$$

The eigenvalues of the canonical system $\tilde{F}$ are identical to the eigenvalues of the canonical system F, which are obtained from the characteristic equation in prony analysis. Eq.33 shows the relation between eigevalues of the system, Q matrix, and H matrix. By focusing on λ_i as a critical mode in presence of oscillations, one can shift them to acceptable location, by setting the values of corresponding q_{ii} as follows.

$$|sI - \tilde{F}| = 0 \tag{31}$$

$$((s + \lambda_i)(s - \lambda_i) - \tilde{q}_{ii}h_{ii}) \prod_{\substack{k=1\\ k\neq j}}^{n} (s + \lambda_k)(s + \lambda_k) = 0 \tag{32}$$

$$q_{ii} = \frac{s_i^2 - \lambda_i^2}{h_{ii}} \tag{33}$$

It is notable that, process of calculating Q_{ii} is dependent on closed loop location of eigenvalues which is, itself, dependent on the control action. The proposed iterative procedure for calculating Q matrix, eigenvalues, and control actions is illustrated in Fig.1. This figure presents the overall proposed control architecture of offline and online energy function estimation, the link to intelligent ACD based control, and the training process of NN blocks of ACD.

V. Implementation and Test results

The architecture discussed in this paper is to modify HDP approach based ACD towards a wide-area controller design with better applicability. It is known that inter-area response may be more effectively damped through the use of WAMs especially with the advent of Global Positioning System (GPS) and PMU technology [22]. Fig.1 presents the overall proposed WASCCO architecture for offline and online energy function estimation, the link to intelligent ACD based control, and the training process of NN blocks of ACD. The action estimated in the online implementation stage is supplemented to excitation control of generators.

Intelligent system construction starts with offline training to set the initial weights for online implementation. In this regard, a batch learning structure with pseudo random inputs and related outputs of the power system model is captured and fed to data base. The training of Action is initialized with the target of local Power System Stabilizer (PSS). Next, Critic NN is updated based on the proposed method, followed by Action

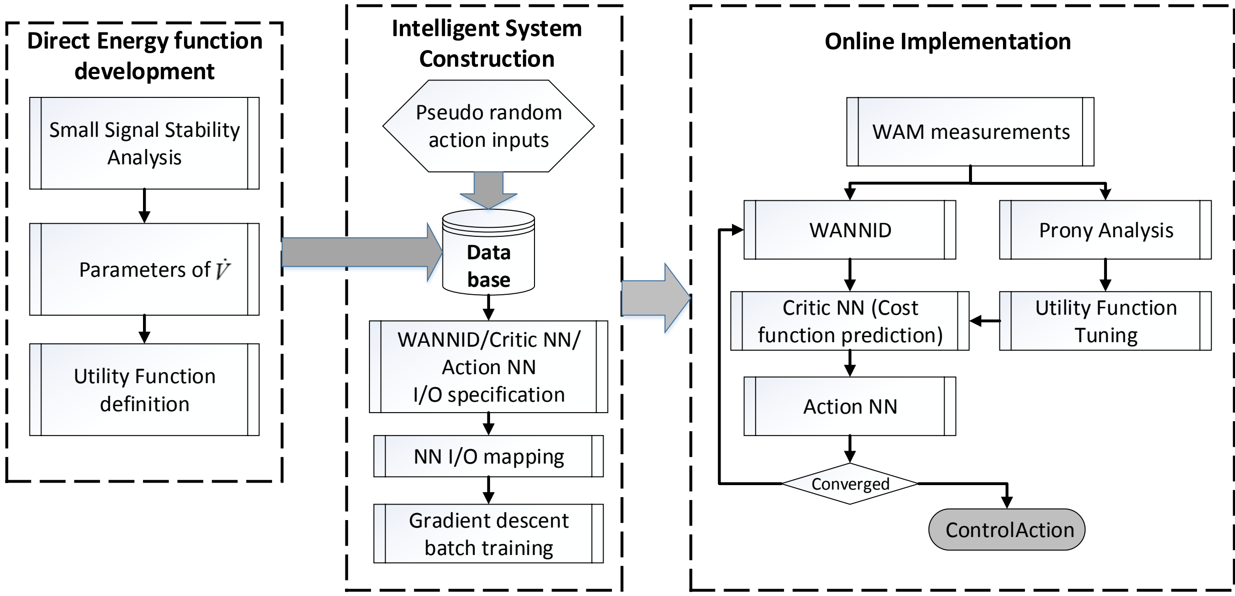

Fig. 1: Overall architecture of proposed WASCCO

update, alternatively. Once the Critic NNs and Action NNs weights have converged, the Action NN is connected to the generator's exciter to replace the PSS. The process of online training starts by monitoring the states to incrementally train the WANNID followed by Critic and Action update iterations (Fig. 1). The Critic training is based on utility function which is tuned online to shift the eigen values derived by Prony analysis to preferred left side plane locations.

It is bear noting that with the advances in PMU and WAM technologies it is possible to monitor the internal variables and parameters of generators. Yet, for the sake of simplicity, in this simulations terminal voltage has been utilized, instead of internal voltage of generators. For analysis of the proposed architecture, two power systems has been considered: a five-machine eight-bus power system without infinite bus, and 68-bus 16-machine IEEE power system.

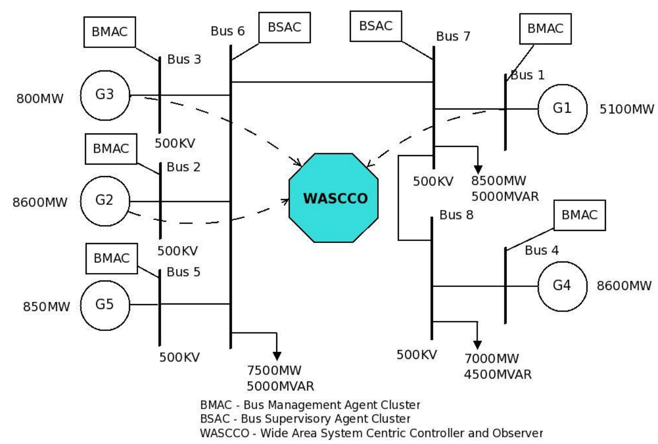

Fig. 2: One-line diagram of the test power system

A. Implementation on a Two Area System

First system is a five-machine eight-bus power system without infinite bus which is modeled using PSCAD. The one-line diagram of the proposed network is shown in Fig. 2. All generators are equipped with governors, exciters, Automatic Voltage Regulators (AVRs), and conventional PSS. Parameters of all devices and operating conditions are given in the [18]. G2, G3, and G5, may be considered to form one area, while generators G1 and G4 form a second area. The two areas are connected through a tie-line (buses 6 and 7).

Performance of the proposed control algorithm has been compared to local PSS and conventional HDP based WASSCO. In this case study, a 100ms three-phase short circuit on the transmission line between bus 6 and bus 7 is simulated. In order to access the performance of the controllers in presence of inter-area oscillations, the line is disconnected by means of breakers. This case study effects all oscillatory modes of the system and changes the topology as well. Inter-area oscillation in this case are presented in Fig. 3. As it can be seen, a notable damping improvement is gained, when the proposed control algorithm has been used. Undershoot of oscillation is reduced 9% in comparison to conventional WASSCO. When there is fault on tie line, the parallel line would encounter a power flow oscillation, as well transmitting the extra 360 MW, which can be seen in Fig. 4. As it can be seen, by utilizing this controller, power transfer margin can be increased by 8.2% in comparison to classical WASSCO and 13.8% in comparison to local PSS.

Eigenvalue monitoring based on Prony analysis for the proposed case study is illustrated in Fig.5. As shows in this figure, when there is a three-phase short circuit fault on the tie-line, states from both areas are activated. Fig.6 shows corresponding changes in the Q matrix with R value, weighting factor of action, set to 0.1.

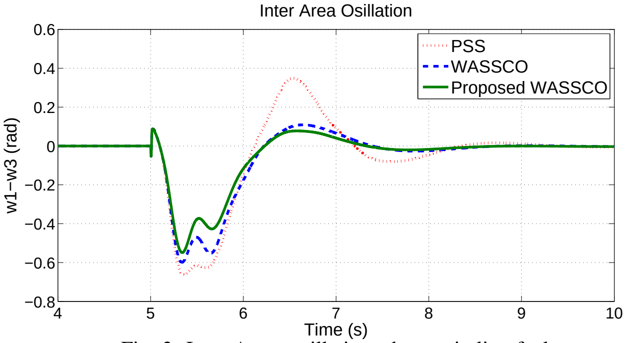

Fig. 3: Inter-Area oscillations due to tie-line fault

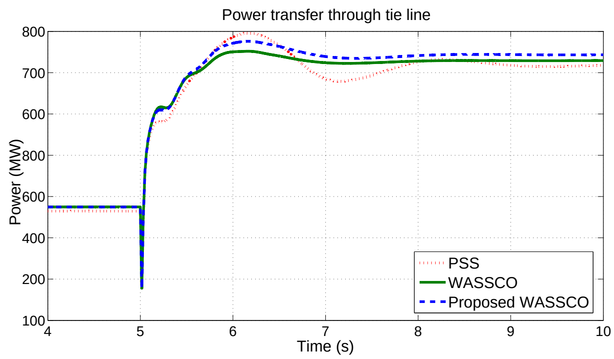

Fig. 4: Power flow oscillations during fault

B. Implementation on a 68-bus 16-machine Power System

In order to assess the capability of the proposed method in comparison to conventional existing transient stability damping controllers, larger scale power system of 68-bus 16-machine test power System has been simulated in PST toolbox. The 68-bus system is a reduced order equivalent of the inter-connected New England test system and New York power system, with five areas out of which New England and new York are represented by a group of generators whereas, the power import from each of the three other areas are approximated by equivalent generator models, as shown in Fig. 7. A brief

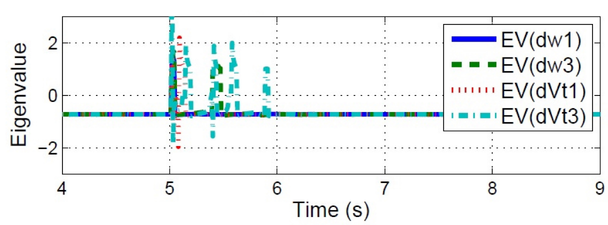

Fig. 5: Eigenvalue changes in states

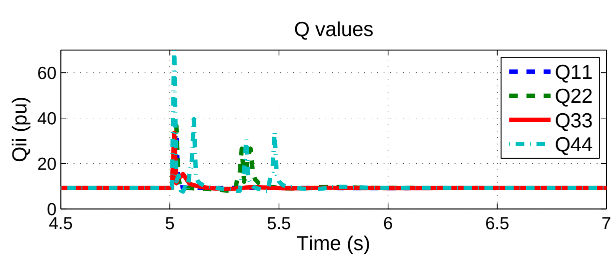

Fig. 6: Online tuning of Q

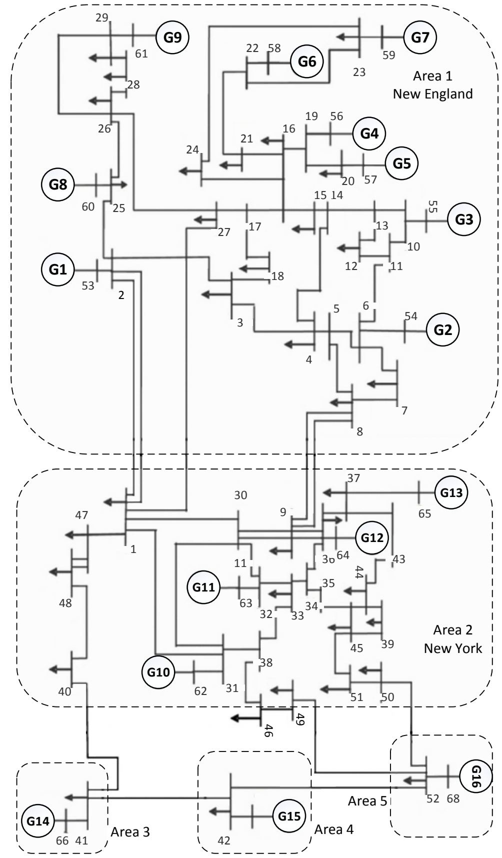

Fig. 7: Single line diagram of the 68-bus 16-machine New England/New York power system with areas and sub-areas

description of dynamic component modeling and its governing equations are presented in [23]. In this simulation, the slow-dynamics of the governors are ignored. Two types of AVRs for the excitation of the generators: IEEE standard DC exciter (DC4B), and the standard static exciter (ST1A). In order to damp the local modes of oscillations, PSS is supplemented to excitation control of generators with the feedback signal of the rotor speed.

It is assumed that each generator bus or substation has a PMU sensor that transmits voltage and speed data to the local phasor data concentrator. The corresponding voltage and angle will be sampled, typically with a sampling rate of 1 point per cycle. In order to overcome the scalability issue of this model, coherent groups has been considered instead of each generator alone. Signals of each coherent groups are aggregated in a manner that the energy function would be the same. Therefore, each aggregated area would be represented by average speed, voltage, and coefficients, as

$$D_j^{av} = \sum D_i \tag{34}$$

$$\Delta\omega_j^{av} = \sum D_i \Delta\omega_i / \sum D_i \tag{35}$$

where, j is representative of area. The same applies to terminal voltages and its relative coefficients.

In this test simulation, performance of the proposed control algorithm has been compared to local PSS and conventional

TABLE I: Electromechanical Modes of the 68-bus System without PSS and Participating Generators

Damping ratio (%)	frequency (Hz)	Gen/pf	Gen/pf	Gen/pf
-0.438	0.404	G13/1	G15/0.556	G14/0.524
0.937	0.526	G14/1	G16/0.738	G13/0.114
-3.855	0.61	G13/1	G12/0.137	G6/0.136
3.321	0.779	G15/1	G14/0.305	x
0.256	0.998	G2/1	G3/0.913	x
3.032	1.073	G12/1	G13/0.179	x
-1.803	1.093	G9/1	G1/0.337	x
3.716	1.158	G5/1	G6/0.959	x
3.588	1.185	G2/1	G3/0.928	x
0.762	1.217	G10/1	G9/0.426	x
1.347	1.26	G1/1	G10/0.756	x
6.487	1.471	G8/1	G1/0.435	x
7.033	1.487	G4/1	G5/0.483	x
6.799	1.503	G7/1	G6/0.557	x
3.904	1.753	G11/1	x	x

TABLE II: Configuration of Neural Networks

NN	Inputs	Delays Layers	Hidden	Outputs	Input Signals	Output Signals
WANNID	30	2	35	10	w,V,u	w,V
Action	20	2	25	5	w,V	u
Critic	20	2	30	1	w,V	J

WASSCO with static weights of 0.5. First, small signal stability analysis has been performed to derive the damping ratio, frequency, and participation factors of the generators in the dominant oscillatory modes (Table. I). This modes has been derived without the presence of any PSS in the system, and it is also provided in [23]. It can be seen that, all the inter-area modes have high participation from machines G13 to G16, and the local modes have high participation from the corresponding local machines. Table II provides the NNs parameters used which are identified in a heuristic manner. This training has been done by means of Matlab NN toolbox, and the weights and parameters are extracted to further use in online implementation.

In this case study, a self healing 100ms three-phase short circuit on the transmission line between area 1 and area 2 is simulated. As it can be seen, in the figure of the system, there are three tie lines connecting these two area: Line 1-2, Line 1-27, and Line 8-9. Fault at each of these tie lines and disconnecting them from the connecting buses leads to inter-area oscillations. Table III presents the overshoot improvement in the case of proposed WASCCO being in the system. It should be noted that these faults are sequentially, meaning that at the end of the sequence these two areas are completely disconnected. Figs. 8 and 9 depict the oscillation of inter-area speed and energy exchange when lines 1-27 and 8-9 are disconnected, and three phase short circuit occurs in the middle of line 1-2. As it can be seen, speed oscillations in presence of proposed method has more damping than local PSS and conventional WASCCO, with less energy exchange, leading to more stability margin.

VI. Future Works and Challenges in Real Time Simulation

The proposed WASCCO for transient stability improvement can be efficiently implemented on a TI board. In our previous work, [24], we have reported successful real-time hardware implementation of optimal power system wide-area system-centric controller based on temporal difference learning. The software and hardware real-time platform is depicted in Fig. 10. For real-time development of the WASCCO, the pre-training stages can be executed offline using the data points obtained from the power system modeled in PSCAD. The modeled power systems is then connected with exciter acting as a 'nominal' controller. The input of the exciter is then connected to the control architecture implemented in Texas Instrument (TI) Controller board, Piccolo C28335. For this, MATLAB codes was first converted to SIMULINK and then to C language by means of Code Composer Studio software which is then deployed to TI controller board. The full description of the implementation method is provided in [24]. The main challenge in this work, in general, all the wide-area controller implementation is the mater of scalability. We seek to tackle the problem with the idea of performing online coherency by means of energy technique provided in this paper, and reduce the data load. Here, the coherent groups were fixed and provided offline. Our next step would be tuning and detecting this coherent groups as well. In addition, the stability proof of the WASCCO is beyond the scope of this

TABLE III: Overshoot of Inter-Area oscillation of Average Speed Between Areas 1 and 2

Case study	PSS	Conv. WASCCO	Proposed WASCCO
Fault at line 8-9	8.991e-4	8.979e-4	8.970e-4
Fault at line 1-27	2.598e-4	2.461e-4	2.181e-4
Fault at line 1-2	7.982e-4	7.768e-4	7.200e-4

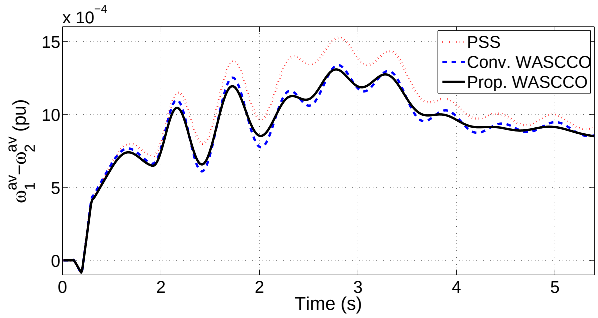

Fig. 8: Inter-area oscillation of speed between area 1 and 2 due to short circuit at line 1-2

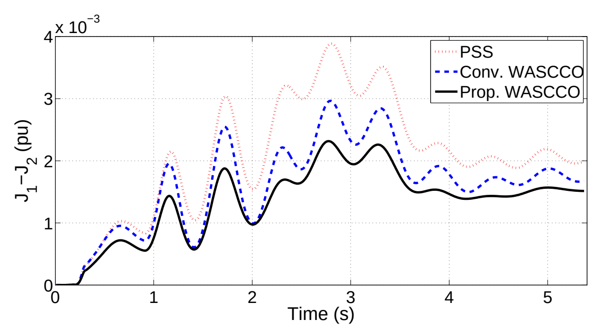

Fig. 9: Inter-area oscillation of Energy exchange between area 1 and 2 due to short circuit at line 1-2

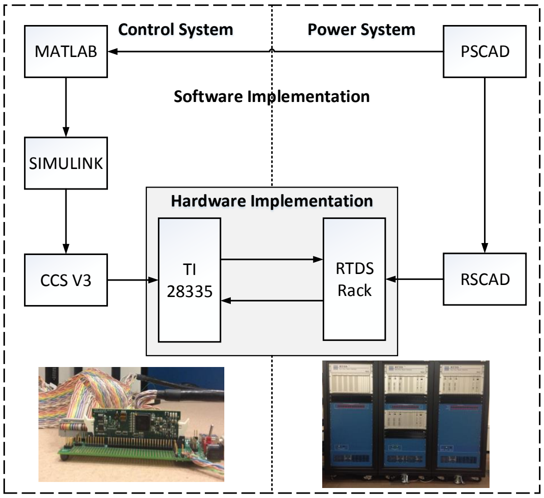

Fig. 10: Real-Time implementation flowchart

paper. Yet, there is not any of a difference to conventional NN-based WASCCO.

VII. Conclusion

In this paper a new energy-based intelligent system centric control design for improved power system transient stability is presented. The algorithm is an optimal Wide-Area System-Centric Controller and Observer (WASCCO) based on Adaptive Critic technique (ACD). Cost function defined in ACD problem are analyzed with Lyapunov stability function to address inter-area oscillations. Further more, an offline and online tuning method is designed based on extracted eigenvalues using small signal stability analysis and Prony analysis and is linked to performance index generation. Results on a two area system and 68-bus 16-machine system shows better response compared to conventional schemes.

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