# Hybrid Transient Energy Function Based Real-Time Optimal Wide-Area Damping Controller

Reza Yousefian, Student Member, IEEE, Amireza Sahami, Student Member, IEEE, Sukumar Kamalasadan, Member, IEEE

Abstract—This paper presents a real-time wide-area damping controller designed based on a hybrid intelligent and direct method to improve power system transient stability. The algorithm applied as a nonlinear optimal Wide-Area Damping Controller (WADC) monitors the oscillations in the system and optimally augments the local excitation system of the synchronous generators. First, energy functions and Prony analysis techniques are used to identify these local or interarea oscillations and develops stability or damping performance index at a given time. Second, artificial Neural Networks (NNs) are deployed to learn the dynamics of the system and energy functions based on supervised learning to construct an optimal control design. Then, using online Reinforcement Learning (RL) the quadratic objective function based on the stability index is estimated and optimized forward-in-time. Results on the IEEE 68-bus in PST and HYPERSIM real-time simulator shows better transient and damping response when compared to conventional schemes and local power system stabilizers.

Keywords—Artificial Intelligence, Energy Function, Neural Network, Real-time Simulation, Transient Stability, Wide-Area Damping Control.

#### I. INTRODUCTION

**M** ODERN power systems are grown into more complex and inter-connected network due to the integration of distributed energy resources, severe transmission congestion, and deregulation of energy markets. Electro-mechanical oscillations exhibited by such power grid has shown increased local and inter-area modes. Local oscillations are due to individual generators swinging relative to the power grid, whereas the inter-area modes are because of group of generators swinging against each other. Conventionally, Power System Stabilizers (PSS) are used to damp such oscillations [1]. However, during inter-area oscillations, PSS designed based on rotor angle small signal stability analysis are prone to failure [2]. Under such scenarios, Wide-Area Damping Control (WADC) system can actively damp inter-area oscillations by coordinating the actions of a number of distributed agents using Wide-Area Monitoring (WAM) information.

Most of the works in this area have utilized classical frequency domain based techniques in the form of Global PSS (GPSS) by incorporating additional remote signals to the local controllers [3]. Such methods rely on modal controllability and observability residues with a-priori passivity information for sensor and actuator locations [4]. However, the complexity of the large scale power system makes such analytical control techniques impractical. In addition, majority of these works are designed based on the model of the system linearized around a particular operating point. This arises the

issue of generality, i.e. the proposed techniques are suitable only for a specific application. Additionally, these modelbased techniques are not able to damp the oscillations in transient domain when power system is subjected to severe disturbances. Application of WAM in real-time disturbance analysis and electro-mechanical mode estimation has been studied in literature [5], [6]. Furthermore, the temporal information can be used in WADC designs to perform transient stability enhancement, which can improve the power transfer capability of a transmission system and prevent the system from generation or load disconnection, or catastrophic failure in the system [7].

1

Traditionally, numerical methods and energy function based direct methods have been the most important conceptual frameworks for real-time transient stability assessment. However, numerical methods have shown considerably weak performance in real-time implementation, as they require accurate information of the power network topology; while, direct methods may lead to excessive simplifications. Such problem formulation provides only the sufficient conditions for assessing the stability using direct calculation of the transient energy function [8]. Although some control techniques based on energy methods have been proposed, such as the Boundary of stability region based Controlling Unstable equilibrium point (BCU) [9], still the computational modeling complexity is considered as a challenge. On the other hand, application of intelligent-based techniques has been successfully investigated in recent literature for post-fault transient stability assessment and power system control [10]-[13]. Decision Tree algorithms, Fuzzy Logic techniques, Neural Networks (NNs), and Support Vector Machines (SVMs) are among these methods that effectively learn and map the system dynamics from the relationship between specified inputs and outputs without any prior knowledge of the system. Most of the works in this area has been designed for classification and remedial action schemes using supervised learning algorithm in order to predict the post-fault stability status.

This paper aims to design an optimal WADC to enhance the transient stability of the system in online/real-time application. There are mainly three issues critical to such a measurementbased control designs. First, the design should have the capability of dealing with nonlinear and nonstationary power system dynamics in the presence of uncertainities. Second, the method should satisfy closed loop system stability and global optimality conditions. Finally, it should be able to project actual stability condition of the system, guaranteeing the stability of the power system augmented with the online control schemes; i.e. ensuring the gradient of the cost-to-go function is decreasing over the time.

In order to address the first issue, Reinforcement Learning (RL) technique is used to train the artificial intelligence. This approach, as opposed to supervised method can make use of the new knowledge to inturn improve learning in real-time during the course of events and actions. This technique can find optimal solution to the cost function by means

This work was supported in part by the National Science Foundation under the grant NSF Grant ECS-1229598 and ECS- 1309911.

R. Yousefian, S. Sahami and S. Kamalasadan (corresponding author), are with the Power, Energy and Intelligent Systems Lab, Department of Electrical Engineering, University of North Carolina at Charlotte, Charlotte, NC 28223 USA (e-mail: ryousefi@uncc.edu, asahami@uncc.edu, skamalas@uncc.edu).

of Adaptive Dynamic Programming (ADP) forward-in-time and provide an effective benchmark to construct an optimal controller by exploiting function approximators, e.g. NNs [14], [15]. It has been implemented as power system controller in several research works. For instance, [16] proposed realtime decentralized wide-area control scheme based on Q-Learning for excitation control of generators. In [17], [18], RL technique is used for damping a single machine and wide-area systems. Ref. [19] presented an optimal wide-area controller and a state predictor for power system with static compensators by employing this method in real-time on radial basis function networks in presence of WAM constraints. In [20] RL has been employed as a WADC on real-time benchmark with wider horizon of prediction to take account for WAM delays. Major disadvantages noted in such designs are strictness of global optimal solution, the objective function definition, and the need for extensive offline training requirements.

Recently it has been shown that RL could be used as an optimal controller guaranteeing global optimal conditions for a non-convex functions [21]. Taking advantage of such a design, in this paper, we show a method that mitigates the last aforementioned issue. In the proposed hybrid approach, the cost function in RL problem is defined based on the energy function damping and tuned online based on Prony method to ensure that the most suitable energy function is estimated. The controller is designed in order to ensure that the gradient of the cost function is strictly negative and minimized over this time period. Consideration of RL based method is due to the fact that for a given time duration it can reach to the global optimal solutions in a nonlinear and uncertain environment [21]. Since the cost function is derived based on energy functions, unlike in conventional methods where it is updated by the Euclidean norm of the desired states, this method guarantees the system convergence to post-fault equilibrium. This is due to the fact that the proposed energy function is utilized to screen the level of stability of the system.

In summary, the construction of WADC is initialized based on offline data derived from direct energy method and supervised learning. This design is further adapted to RL for online implementation and policy iteration with only partial knowledge of system dynamics. One of the main advantages of the proposed method, as shown in [12], is that the NNs would be able to capture the underlying relationship with smaller sized training data set and with higher accuracy when meaningful energy features are used as inputs. Moreover, through deployment of RL and by monitoring the system modes online the control scheme can be performed in realtime as well. This method is evolved from [22] for realtime wide-area monitoring and control of large power system. The remainder of the paper is organized as follows. The second section presents system modeling and direct energy function development and Section III discusses the proposed optimal WADC design. Section IV and V present the power and control systems implementation test bed and simulation results followed by conclusions in section VI.

# II. SYSTEM MODELING AND DIRECT ENERGY FUNCTION DEVELOPMENT

Considering  $x^*$  is the reference equilibrium point of the dynamic system expressed in the form of nonlinear continuoustime equations

$$\dot{x}(t) = f(x(t)) + g(x(t))u(t)$$
 (1)

2

(4)

then  $f(x^*(t)) = 0$ .  $x(t) \in \mathbb{R}^n$  and  $u(t) \in \mathbb{R}^m$  are the state vector and the control action vector at time t, respectively, and f and g are nonlinear functions. Let J(t) be an energy function of trajectory x at a particular time t, the system (1) is asymptotically stable when

$$J(x(t)) \ge 0, \quad J(x(t), u(t)) \le 0$$
 (2)

Based on this, the sufficient conditions for stability assuming this energy function model can be evaluated and the candidates Lyapunov function can be developed to mathematically prove convergence of the system to the reference operating points  $x^*$ . This dynamic and energy function is developed next for synchronous generators in transient disturbances. Furthermore,  $\dot{J}$  is studied to investigate the damping performance of the oscillations in time.

## A. Area Oscillation Modeling

In the context of rotor angle stability, the dynamics of each synchronous generator bus can be can be characterized by the complex terminal voltage  $V_t \angle \delta$ , where  $\delta$  is the rotor angle with respect to synchronously rotating reference frame. The rotor speed is given by  $\delta$ . A weakly coupled power network does not display any coherent oscillation behavior, whereas a strongly coupled network with sufficiently homogeneous natural frequencies is amenable to synchronization in the form of coherent areas. Hence, slow coherency technique based on Center Of Inertia (COI) can be employed to cluster the generators in one area [23]. Let a state space vector  $x = [\delta_1, ..., \delta_N, \dot{\delta}_1, ..., \dot{\delta}_N]^T$  be composed of the vector of coherent generators rotor angle and speed, with  $\mathcal{N}$  being the total number of areas. The dynamics of the equivalent generators can be described through the expansion of the electro-mechanical single generator model [24]. Additionally, in order to incorporate the impacts of damping controller the third order dynamics of the generator is also included in this paper as:

$$m_j \ddot{\delta}_j + d_j \dot{\delta}_j = P_j - \sum_{k \in N_j} B_{jk} E'_{qj} E'_{qk} \sin(\delta_{jk})$$
(3)

 $T'_{doj}\dot{E}'_{qj} = \tilde{E}_{fj} - \tilde{E}_{qj}$ 

with

$$\delta_j = (1/m_j) \sum_{i=1}^{n_{g_j}} m_i \delta_i, \quad \dot{\delta}_j = (1/m_j) \sum_{i=1}^{n_{g_j}} m_i \dot{\delta}_i \quad (5)$$

$$m_j = \sum_i^{N_{j_j}} m_i, \quad P_j = \sum_i^{N_{j_j}} P_i \tag{6}$$

where,

$\delta_{j}$	Area $j$ rotor angle in COI frame;
~	Deviation of the variables from the reference;
$\dot{\delta}_{j}$	Area $j$ rotor (electrical) speed in COI frame;
i, j	Generator and area index;
$n_{g_i}$	Number of generators in the area $j$ ;
$N_j$	Set of neighboring buses of the $j^{th}$ bus
m,d	Inertia and damping parameters;
$P_i$	The power injection from area $j$ ;
$\check{B_{jk}}$	(j,k)th entry of the reduced lossless admit-
	tance matrix;
$E_q, E'_q$	The q-axis internal voltage and transient emf;
$T_{do}^{\prime}$	The open-circuit transient time constant;
$E_f$	Excitation voltage;

The transient instability, in general rotor angle oscillations, is caused by a mismatch between injected power  $P_j$  of each unit and the power flows along the transmission lines



Fig. 1: Linear and nonlinear energy function representation

 $\sum_{k \in N_j} B_{kj} E'_{qj} E'_{qk} \sin(\delta_{jk})$ . This mismatch is usually due to a fault on power system lines or other components, which is followed by the action of protection system. These actions may change or restore the topology of the system, which leads to a transition from pre-fault to post-fault equilibrium points. The transition can be viewed from energy landscape to investigate the convergence as well as damping performance.

## B. Energy Function

Power system rotor angle stability can be assessed by the ability of the synchronous machines in absorbing or releasing the energy accumulated during a disturbance to reach a post-fault equilibrium points. An energy-type Lyapunov function for such a system model comprises of the sum of the system kinetic energy and potential energy with respect to the relevant equilibrium points  $\delta_j^*$  and  $\delta_j^*$ . Such a function can be represented as,

$$J(\delta, \dot{\delta}) = \sum_{j} \underbrace{\frac{1}{2} m_{j} \dot{\tilde{\delta}}_{j}^{2}}_{J_{K_{j}}} (7)$$

$$- \int_{\delta_{j}^{*}}^{\delta_{j}} P_{j} d\delta_{j} + \int_{\delta_{j}^{*}}^{\delta_{j}} \sum_{k \in N_{j}} B_{jk} E'_{qj} E'_{qk} \sin \delta_{jk} d\delta_{jk}$$

$$J_{P_{j}}$$

where,  $\tilde{\delta}_j = \delta_j - \delta_j^*$  denotes the deviation from post-fault equilibrium point.

It should be noted that, decreasing nature of the energy function provides the main certificate of local stability; however, it is not the only function that can be linked to decrease in the energy dynamics around a given equilibrium point  $\delta^* =$  $[\delta_1^*, ..., \delta_N^*]$ . Thus the key is to find a Lyapunov function and verify that it has the required stability properties regarding the domain of state trajectory. It could be understood from (7) that the stability depends on the system pre- and post-fault conditions. It can be shown that these equilibrium points satisfy the net power in each area as  $P_j = \sum_{k \in N_j} B_{jk} E'_{qj} E'_{qk} \sin \delta^*_{jk}$ . If the changes of the states are in small-signal domain the nonlinear part of potential energy could be linearized around the operating point as  $(\delta_j - \delta_j^*)^2$ ; whereas, in the case of severe transient changes the post-fault points falls into a nonlinear region. The transient problem involves finding the stability boundary which is highly nonlinear. This feature shown in Fig. 1, is important for convergence and stability certificate as it can be proved that there exist a boundary that nonlinear energy function has positive and strictly decaying behavior in the region, meaning here the  $\delta_i$  converges to the stable global optimal point  $\delta_i^*$ .

# C. Energy Function Damping

In general, rotor oscillations of increasing amplitude due to lack of sufficient damping torque can lead to instability [25]. In order to incorporate the impacts of excitation control another term is added to energy function so-called field or control energy [26] based on internal voltage:

$$J_{Fj} = \frac{1}{2}\beta_j (\tilde{E}'_{qj})^2 \tag{8}$$

to capture the damping of the energy with respect to time, the derivative of the kinetic, potential, and field energy function is derived and can be simplified as,

$$\dot{J}(\dot{\delta}, E_q, E_f) = -\sum_j d_j \dot{\tilde{\delta}}_j^2 + \frac{1}{T'_{d0j} \Delta X_{dj}} (\tilde{E}_{qj}^2 + \tilde{E}_{qj} \tilde{E}_{fj}) \quad (9)$$

with the assumption on higher orders of synchronous generator as  $\tilde{E}_f = K\tilde{E}_q$ ,  $\tilde{E}_q = X_{ad}\tilde{i}_f$ , and  $\tilde{i}_f = K'\tilde{V}_t$  with the gains K and K' > 0,  $\tilde{i}_f$  as a field current deviation, and  $\tilde{V}_t$ as the terminal voltage deviation or the control input to the field component, (9) yields

$$\dot{J}(\dot{\delta}, V_t) = -\sum_j d_j \dot{\tilde{\delta}}_j^2 + r_j \tilde{V}_{tj}^2.$$
(10)

with  $r_j \equiv \frac{1+K_j}{T'_{doj}\Delta X_{dj}}X^2_{adj}K'_j$ , which can be derived based on aggregated model of synchronous generators [24]. This equation reveals that the states needed to monitor the transient energy deviation of each area is the  $\dot{\delta}$ . The impact of each area's state on the inter-area oscillation is projected by the damping coefficients  $d_j$ . Overall, damping of interarea oscillations depends on the strength of the transmission system, generator control systems and dynamics of inertia-less generators. Even though this parameter is fixed to individual generator, for the system as a whole the damping coefficients may be changing not be known precisely at given time of interest and is needed to be calculated. Identification of energy function considering the actual oscillation frequency and damping parameters can further improve the performance of the controller.

Another observation in the above equation is the impact of  $\tilde{V}_t$  as the input to the synchronous generator excitation field. This input without controllers is the error between the reference and the terminal voltages of the generator  $(u = \tilde{V}_t)$ . However, this signal can be augmented by local and wide-area control to further improve the energy function damping.

#### **III. INTELLIGENT WADC CONSTRUCTION**

In this section, the goal is to develop an optimal intelligent WADC to stabilize and damp the inter-area oscillations occurring in power system. As mentioned in previous section, the input to the synchronous generator excitation field could be augmented with  $u_{loc}$  as local damping signal derived from PSS and enhanced by  $u_{wac}$  as a wide-area level damping controller. Hence, the control action can be presented as 2level combination of local and wide-area parts as

$$u(t) = u_{loc}(t) + u_{wac}(t) \tag{11}$$

as shown in Fig. 2. The PSS monitoring the local states is able to damp local oscillations; while, the WADC monitoring rotor angle and speed of all generators using wide-area measurements in COI frame can form the system's energy function (7) and its damping (10) as in direct methods and enhance the damping performance by  $u_{wac}$ .



Fig. 2: Structure of the 2-level control design combining local and wide-area damping control (TDL: time delay line, LC: local control)

#### A. Optimal Control Design

Considering the transient energy function developed in previous section as the cost function, optimal controller can be designed to minimize this energy function forward in time. Overall, the cost function can be implicitly specified in discrete time domain with the time step of  $\Delta t$  by

$$J(x(k)) = \sum_{\tau=k}^{\infty} \dot{J}(x(\tau), u(\tau))$$
(12)

where, k is the time step index and J is the short-time cost function associated with transient state errors and control effort equivalent to derivative function in Lyapunov stability concept. Hence, it can be written as,

$$\dot{J}(x(k), u(k)) = -\tilde{x}(k)^T Q \tilde{x}(k) - u(k)^T R u(k)$$
(13)

where,

$$x = [\delta_1, \dots, \delta_{\mathcal{N}}, \dot{\delta}_1, \dots, \dot{\delta}_{\mathcal{N}}]^T \tag{14}$$

$$u = [\tilde{V}_{t1}, ..., \tilde{V}_{tN}]^T$$
 (15)

$$Q = \operatorname{diag}(0, ..., 0, d_1, ..., d_{\mathcal{N}}) \in \mathbb{R}^{2\mathcal{N} \times 2\mathcal{N}}$$
(16)

$$R = \operatorname{diag}(r_1, \dots, r_{\mathcal{N}}) \in \mathbb{R}^{\mathcal{N} \times \mathcal{N}}$$
(17)

which are based on actual values of coefficient of (10) and are positive definite. One can simply use these functions and assess transient stability based on direct methods and design decentralized controller such as in [26]. However, such designs are not global optimal. The optimal solution of the problem of (12) subjected to the dynamic system (1) is given by minimization of HJB equation as,

$$u^{*}(k) = \arg\min_{u} \{J(x(k), u(k)) + J(x(k+1))\}$$
(18)

Applying the first order optimality conditions with the dynamic programming algorithm leads to,

$$u^*(k) = -1/2R^{-1}\frac{\partial x(k+1)}{\partial u(k)}\frac{\partial J(x(k+1))}{\partial x(k+1)}$$
(19)

It can be seen from equation above that the optimal control action  $u^*(k)$  is defined on the future dynamics of the system x(k+1) and the energy function J(x(k+1)), which implies the necessity of nonlinear identification. Additionally, the energy function itself is highly dependent on the parameters of

the system such as m, B, or  $\beta$ , even though simplified model of the system without structure preserving is considered in the design. In order to overcome these issues and cover nonlinear regions, artificial intelligence is employed 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 scheme, three networks called *identifier*, *critic*, and *action* NNs are trained to approximate the dynamics of the system, the control action, and the cost function, respectively. In this work, using Feed Forward Neural Network (FFNN) the outputs are computed as,

$$\hat{x}(k) = W_I(k)^T \Phi_I(x(k-1), u(k-1)) + \epsilon_I(k)$$
(20)

$$\hat{u}(k) = W_A(k)^T \Phi_A(x(k)) + \epsilon_A(k)$$
(21)

$$J(x(k)) = W_C(k)^T \Phi_C(x(k)) + \epsilon_C(k)$$
(22)

where, sub-scripts I, A, and C denotes identifier, action, and critic networks, respectively, "^" denotes estimated values,  $\Phi(.) \in \Re^h$  is the corresponding nonlinear mapping function of the states,  $W(k) \in \Re^h$  is the parameter vector of approximated weights of the FFNN at time step k, with  $h \in \mathbb{N}$ dimensionality of the feature vector representing each state, and  $\epsilon$  is the approximation error. Based on the universal approximation property of NN it is assumed that  $\epsilon$  tends to zero [27, p. 52].

NNs should be trained to provide accurate approximation of their respective outputs and back-propagation estimation and cover whole region of operations. In general, training the NNs means adjusting the parameters or weights in an iterative process to reduce the error between the target outputs and the actual outputs. Intelligent WADC construction could be implemented in two phases:

## B. Offline Supervised Learning Construction

This method is referred to problems involving static input/output mappings and minimization of a vector error signal, with no explicit dependence on how training examples are gathered. It is assumed that full knowledge of the problem context is available. In offline phase the parameters and operating point are known; hence, the target output for training the NNs could be calculated. The supervised training for WADC are based on the following errors:

$$e_I = \sum_k x(k) - \hat{x}(k) \tag{23}$$

$$e_C = \sum_k J(x(k)) - \hat{J}(x(k))$$
 (24)

$$e_A = \sum_k u^*(k) - \hat{u}(k)$$
 (25)

where, "^" denotes estimated values based on (20)-(22). The training process of the critic NN is performed with the target of conventional energy function (7). The post-fault equilibrium point can be calculated simply based on the post-fault load flow to derive this function. Further, the training of the action NN is based on optimal control derived in (19). It should be noted that, the two derivative elements in (19) are simply calculated by propagating the respective output back through the identifier and critic NNs.

Change of the NNs weights at each iteration i can be derived from the deviation of NN's output to its optimal value  $e^i$ . In offline training, batch learning is performed in which

adjustment of the weights are accumulated over all training data to give an aggregated error as,

$$\hat{W}^{i+1} - \hat{W}^i = \alpha e^i \Phi(.) \tag{26}$$

where,  $\alpha$  is a small learning rate. This optimization iteration is performed by means of training the NNs through gradient descent via back-propagation. From the viewpoint of optimal control theory, this task is the same as the first-order calculus of variation to find the continuous-time equations derivations.

#### C. Online Reinforcement Learning Construction

In this paper, RL technique is employed for adaptation of artificial intelligence-based WADC in online application. By means of this method, the NNs parameters and weights are updated based on measurements instead of conservative offline assumptions. RL is often applied to problems involving sequential dynamics and optimization of a scalar performance objective, with online exploration of the effects of actions as it can adapt itself to fit the changing environment. The identifier NN is updated online with the monitored states similar to supervised learning; however, different procedure is used for critic and action NNs training. In the RL method cost function at each iteration i is approximated by adaptation of Approximate Dynamic Programming (ADP) as,

$$e_C^i(k) = \hat{J}^i(x(k)) - \hat{J}^i(x(k+1)) - \dot{J}(x(k), u^i(k))$$
 (27)

and, training of the action NN at each iteration is based on

$$e_A^i(k) = 2Ru^i(k) + \frac{\partial \hat{x}(k+1)}{\partial \hat{u}^i(k)} \frac{\partial J^i(x(k+1))}{\partial \hat{x}(k+1)}$$
(28)

and, weight adjustment is done incrementally at each iteration and time step as,

$$\hat{W}^{i+1}(k) - \hat{W}^{i}(k) = \alpha e^{i}(k)\Phi(.)$$
(29)

The stability properties of the ADP is discussed in [21].

# D. Online Energy Function Construction and Tuning

As presented in previous subsection the incremental critic NN training is based on  $\hat{J}(x(k+1))$  and  $\dot{J}(x(k), u(k))$  at each time step. The first element is derived from the critic NN with the input of  $\hat{x}(k+1)$  which is accessible from the identifier NN. The later is derivative of energy function defined in (13) in quadratic form representing the damping of energy function. This function is dependent on d which is characteristic of damping of oscillations of each area's states and needed to be identified online.

The Prony method, the best known parameter identification method in the power system community [28], is used to determine the unknown eigenvalues of the system and extract the damping coefficient features. This method is based on measured global states, x(k), being expressed in z-transform domain as a sum of n damped complex sinusoids,

$$x(k) = \sum_{l=1}^{n} \bar{R}_l z_l^k \tag{30}$$

with characteristic equation of  $z^n + a_1 z^{n-1} + ... + a_n = 0$ , where  $R_l$  is an output residue corresponding to the mode  $\lambda_l$ . The vector  $A' = [a_1, ..., a_n]$  leads to the eigenvalues,  $z_l$ s, 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 are neglected. This analysis leads to obtaining the eigenvalues of the system which is then used to adapt the weighing matrix of the states accordingly. For this purpose, an auto regressive (AR) model estimation method has been employed. One can find a values by solving a least squares problem defined on the 2-norm of a vector with an adaptive algorithm that recursively optimizes the criterion.

$$\min_{a} \| \begin{bmatrix} x(n) \\ x(n+1) \\ \vdots \\ x(n+l) \end{bmatrix} - \begin{bmatrix} x(n-1) & \dots & x(0) \\ x(n) & \dots & x(1) \\ \vdots & \ddots & \vdots \\ x(n+l-1) & \dots & x(l) \end{bmatrix} \begin{bmatrix} -a_1 \\ -a_2 \\ \vdots \\ -a_n \end{bmatrix} \| \quad (31)$$

After computing *a* at time step *k*, roots of the characteristic polynomial is derived to generate eigenvalues  $\lambda_j = -\zeta_j \omega_j \pm \omega_j \sqrt{\zeta_j^2 - 1}$  for global oscillations with  $\omega$  natural frequency and  $\zeta$  damping factor. Further, damping coefficient of area *j* can be derived as

$$d_j = \omega_l \zeta_l m_j \tag{32}$$

Subsequently, Q and  $\dot{J}$  can be updated based on  $d_j(k)$  at each iteration i as,

$$\begin{aligned} Q_{n+j,n+j}^{i+1}(k) &= Q_{n+j,n+j}^{i}(k) + \gamma(d_j^{i+1}(k) - d_j^{i}(k)) \text{ (33)} \\ \dot{J}^{i+1}(x(k), u(k)) &= \tilde{x}(k)^T Q^{i+1} \tilde{x}(k) + u(k)^T Ru(k) \text{ (34)} \end{aligned}$$

where,  $\gamma$  is the scaling factor.

*Remark:* It is assumed that the power system is operating at the same operating point for a certain time that enables the estimated d to converge. It is noted that this is not a constraint in practice, since the estimated model parameters converge to their new values fast enough compared to the dynamics [29].

#### E. Comparison with Other Techniques

In this paper RL method with online tuning has been employed to design the WADC. The advantages of the proposed method over conventional methods are as follows:

- a) Both methods of direct and supervised learning are developed directly on the energy function J, which is defined on the post-fault equilibrium points of  $\delta^*$  and  $\dot{\delta}^*$ . This postfault  $\delta^*$  maybe different than pre-fault  $\delta^0$  due to network reconfiguration after a fault and protection control actions. However, RL method is updated based on  $\dot{J}$  which is only defined on  $\dot{\delta}^*$ . This value is considered 1 pu in both preand post-fault conditions.
- b) Direct and supervised learning methods rely on the parameters of the system such as m and B, which may have uncertainty or be changing in time. RL method on the other hand is capable of updating it's policies over time and under conditions of noise and uncertainty through stateaction interaction [15].
- c) Since actions should be taken at each time step and their effect is not known until the end of the sequence, it is not possible to design an optimal controller in online application using the traditional SL. RL method allows the WADC to account for the present control actions u(k) and *future* consequences on the system in J(x(k + 1)) term used in (27), and *present* consequences in the form of short-time cost function in J(x(k), u(k)) term.
- d) The term J in RL is used for updating the cost function and is called performance function. Monitoring this function directly instead of J is well-suited for the purpose of WADC design as it shows how is the *performance* of the controller in terms of transient energy function damping.



Fig. 3: Single line diagram and polar dominant modes of the 68-bus 16machine New England New York power system.

# IV. IMPLEMENTATION AND TEST RESULTS

## A. Power System Test Case

In order to assess the capability of the proposed method, IEEE 68-bus 16-machine power system has been modeled using Power System Toolbox (PST). The model is a reduced order equivalent of the inter-connected New England and New York power systems with nine areas as shown in Fig. 3. The New England and New York power grids are represented by group of generators, whereas the power import from each of the three other neighboring areas are approximated by equivalent generator models. Grouping consideration is based on the oscillation modes, dynamic data of the generators, and the parameters of the transmission system [30]. Dominant modes of inter-area oscillations can be derived by small-signal stability analysis, which is presented in Fig. 2. In this simulation, the slow-dynamics of the governors are ignored. Two types of excitation systems for the generators is considered: IEEE standard DC exciter (DC4B) and the standard static exciter (ST1A). All generators are equipped with PSS using the parameters in Table I.

## B. Proposed WADC Architecture

Input vector of the WADC is the states derived from WAM  $(\delta(k), \dot{\delta}(k))$  in order to estimate the energy function (J(x(k))), and the output is the optimal damping control  $(\tilde{V}_t(k))$  at time step k. Here, we assume that the communication system can transmit the signals to the control center at the speed of 100 frames/sec; hence, WADC communication time step is considered as  $\Delta t = 10ms$ . It is also assumed that each generating unit bus has a sensor that transmits signals to WADC system. For synchronous generators buses, signals are aggregated in WADC center in COI frame of (5) to generate areas state. Fig. 4 presents the proposed WADC architecture for offline and online energy function estimation, the link to intelligent control, and the training process of NN blocks.

TABLE I: PSS parameters for power system test case

Generator	$K_s$	$T_s$	T1	$T_2$	$T_3$	$T_4$	$T_5$	$T_6$
$G_1:G_8,G_{10}:G_{12}$	20	15	0.15	0.04	0.15	0.04	0.15	0.04
$G_9$	12	10	0.09	0.02	0.09	0.02	1	1

TABLE II: Configuration of Neural Networks

NN	Input (# of nodes)	Output (# of nodes)	# of hidden nodes
Identifier	$\delta, \dot{\delta}, \tilde{V}_t$ (54)	$\delta, \dot{\delta}$ (18)	70
Action	$\delta, \dot{\delta}$ (36)	$ ilde{V}_t$ (9)	50
Critic	$\delta, \dot{\delta}$ (36)	J(9)	50

The construction of intelligent system starts with offline supervised learning in order to set the initial weights for online implementation. The training is performed based on the I/O signals for each of the NNs derived using Matlab NN toolbox. These weights and parameters are extracted in data base for online implementation. Table II lists the NNs parameters used for the study. It should be noted that variables are time delayed by one time step to capture the dynamics of the system. For identifier NN, pseudo random inputs and related outputs of the power system model in COI frame is captured and fed into the NN data base. Then, gradient descent batch learning algorithm is performed with a learning rate of about 0.001. It has been seen that  $e_I$  reaches a small number in 100 epochs. Furthermore, the critic NN is trained based on (7) for different fault scenarios and operating points in multiple time-domain simulations to learn the relative energy functions. Parameters of energy function including m, B,  $\beta$  can be derived from [30]. It should be noted that B is the Kron-reduced susceptance matrix with the loads removed from consideration. Next, action NN is trained (19). Once the NNs weights have converged ( $e_C \& e_A < 0.01$ ), then the action NN is connected to the generator's exciter to augment the PSS.

Online training starts by monitoring the states to incrementally train the identifier NN. This is followed by critic and action update iterations using derivatives of energy function. Here, for the sake of simplicity r is considered as 0.1. Prony algorithm is applied to identify the modes and assess the damping ratios of individual area angular oscillations. For this purpose, the values of  $\delta_j$  is captured at time steps of 5. $\Delta t$  and used for tuning the derivative energy function. Since there are 9 sixth-order areas, the algorithm should ideally solve 54th order polynomial. However, choosing 15th order yields a satisfactory estimates of the inter-area modes.

### V. SIMULATION RESULTS

#### A. Case A. Proposed Method vs Conventional AI Methods

In this case study the damping performance of the proposed hybrid RL and energy-based method WADC design has been investigated. The load connected to bus 25 (224 MW) has been disconnected for 200 ms due to a short circuit fault, creating a local mode of oscillation in area 1. During the fault the area 1 moves away from the pre-fault equilibrium point ( $\delta_{A1}^0 = 0.22$ ). After the re-closing action (t = 0.3s), the system configuration is the same as pre-fault ( $\delta_{A1}^* = 0.22$ ) and the system experiences the post-fault transient dynamics of Fig. 5a. This figure presents during- and post-fault trajectory of the  $\dot{\delta}_{A1}$  in the case of different control scenarios. As shown, the proposed WADC compared to supervised learning algorithm has provided better performance with respect to



Fig. 4: Structure of the wide-area damping control center design



Fig. 5: Case A. Comparison of the proposed hybrid method with conventional supervised and RL: (a) Area 1 speed oscillation, (b) Energy function area 1, (c) Derivative of energy function area 1.

overshoots and damping. The transient energy function dynamics has been demonstrated in Fig. 5b. As it can be seen the proposed WADC is able to provide more damping than supervised learning due to online optimal control adaptation and exploration.

Additionally, the proposed method has been compared to conventional RL-based WADC. The RL method being implemented in several works as a WADC such as in [16]–[20], where the cost function is defined in the form of

quadratic function of states with heuristic coefficients based on linearized model of the system. This definition, however, is not representative of energy function damping as opposed to the proposed hybrid method. The proposed method with the help of Prony analysis can estimate the actual damping coefficient ( $d_1 \approx \hat{d}_1 = 0.821$ ) and subsequently energy function damping performance as shown in Fig. 5c.

# B. Case B. Robustness to Parameters

This test presents a case study to demonstrate one of the motivations for choosing the RL algorithm as the benchmark to perform the online optimal function approximation. Initially, a scenario of cascading failures due to faults on interarea tie-lines has been performed. In this test, three tie-lines connecting New England and New York power systems are disconnected sequentially, separating the two grids at the end. Under nominal condition 1170 MW is transferred to New England system through these tie-lines. First, line 1-27 is disconnected (event 1) followed by line 8-9 (event 2) allowing the RL to gain enough knowledge about system dynamics and optimal policy. Finally, line 1-2 is disconnected due to a selfclearing 100 ms three-phase short circuit fault (event 3), which leads to complete separation of these two systems and huge energy mismatch. The WADC is independently validated for performance and accuracy using two data sets of trained and non-trained NNs. Tables III and IV reveal the advantage of the RL method by allowing the NNs to gain more knowledge about the optimal policy of action and energy during the course of events. In the case of trained NN set, identifier, action, and critic NNs have been trained offline and then used in the WADC. In the other data set, the NNs weights are assigned randomly. In this table, the Root Mean Square Error (RMSE) of the latter is higher; however, it improves with each course of event because of online RL learning. Also it can be seen that the number of iterations during last fault occurrence is less than the first event implying the faster convergence of NNs. For this test, maximum number of iteration at each time step is 100 and minimum error assigned is 0.01.

## C. Case C. Proposed WADC vs Linear Controllers

Further, performance of the proposed WADC for the last event in case B, i.e. fault on line 1-2, is compared to PSS

TABLE III: Case B. Performance of NNs in Trained Dataset

Event	Identifier		A	ction	Critic		
	RMSE	Max Iter.	RMSE	Max Iter.	RMSE	Max Iter.	
1	0.010	100	0.021	100	0.016	100	
2	0.010	71	0.010	83	0.010	84	
3	0.010	43	0.010	54	0.010	55	

TABLE IV: Case B. Performance of NNs in Not Trained Dataset

Event	Identifier		A	ction	Critic		
	RMSE	Max Iter.	RMSE	Max Iter.	RMSE	Max Iter.	
1	0.530	100	0.476	100	0.489	100	
2	0.110	100	0.153	100	0.112	100	
3	0.021	100	0.064	100	0.053	100	

and conventional GPSS with the parameters of  $K_s = 1$ ,  $T_s = 10$ ,  $T_1 = T_3 = 0.6280$ , and  $T_2 = T_4 = 0.1025$  [3], [31] (see Fig. 6). For this test, GPSS uses a single differential frequency signal between two selected areas of 1 and 5 ( $\dot{\delta}_{A1} - \dot{\delta}_{A5}$ ). The parameters are tuned based on small-signal analysis. Fig. 6a demonstrates the modes of the inter-area oscillation with frequency of 0.830 Hz and damping factor of 0.605%. As it can be seen, modes of area 5 has been shifted closer to the area 1 with the proposed WADC. This result is validated for inter-area oscillation as well as local speed deviation as they have been better damped in presence of the proposed WADC. Fig. 6d shows the derivative of energy function with respect to time and in terms of elements of control, local and area states.

## D. Case D. Robustness to Delays

It is worth noting that transfer of WAM measurements to the control center may incur certain time-delays. As a measurement-based control design, neglecting this property of WAM may degrade the performance or even destabilize the control system. Usually, the delay of the WAM signals in a high-bandwidth communication system is expected to be small for the purpose of the WADC design. In [32] the WAM infrastructure and various possible communication delays have been covered. In this case study the robustness of the proposed WADC to possible communication delays has been investigated. All the PMU signals are delayed by 100 ms, which is larger than the expected delay in the realistic system. Fig. 7 shows the system dynamic response of a the system (local and inter-area oscillations) with the same fault scenario as Case C. It can be seen that delays has deteriorated the WADC performance, however, the system oscillations still damp faster than the case without WADC. Moreover, the performance of proposed WADC in the most extreme scenario is evaluated by increasing the delay time in PMU signals. Further simulations showed that the WADC is robust to delays of 350 ms in communication network.

## E. Case E. Real-Time Simulation

In order to investigate the performance of the proposed WAC for real-time transient stability improvement, the New England part of the test system, so-called IEEE 39-bus system has been modeled using real-time simulator Hypersim [33]. The simulation is based on EMTP nodal method capable of running the simulations by parallel computation. The modeled power system generators are connected to exciter and PSS acting as local controllers. These controllers run at the speed of 50 us. For real-time development of the WAC, the offline pre-training stage of NNs is obtained from the power system modeled in PST. The WAC model is then imported



Fig. 6: Case C. Comparison of proposed WADC with conventional PSS and GPSS, (a) Area oscillation modes (b) Local oscillation of G1 ( $\zeta = 0.7805\%, f = 1.8957Hz$ , (c) Inter-Area oscillation of A1 and A5( $\zeta = 0.6054\%, f = 0.83Hz$ , (d) Derivative of energy function.



Fig. 7: Case D. Comparison of proposed 100 ms delayed WADC with conventional PSS and GPSS, (a) Local oscillation of G1, (b) Inter-area oscillation of A1 and A5.

from Matlab-Simulink through the C-code conversion and



Fig. 8: Case E. Real-time dynamic performance of the power and control system, (a) Area Oscillations, (b) Control signals, (c) NNs errors, (d) Damping coefficient approximation with Prony analysis.

deployed in the Hypersim environment. The input of exciter is augmented by the WAC actions running at the simulation time step of 10 ms.

In order to analyze the performance of the proposed architecture, a self-clearing 125ms three-phase short circuit at bus 17 is simulated. This scenario affects all the oscillatory modes of the devices and the network topology. Area speed oscillations of the 4 areas of the test system are presented in Fig. 8a. As shown, a considerable damping improvement is gained when the proposed architecture is adopted. In addition, overshoots and undershoots of oscillation are reduced as well. The local control action of PSS and the WADC are presented in Fig. 8b. Further, Fig. 8c presents the WADC NNs error. As it can be seen the identifier, action, and critic NNs have performed satisfactory in real-time with the maximum error limited to 0.025 pu. It is worth noting that as mentioned before, the critic tuning is performed in real-time using the proposed Prony analysis. The method is capable of identifying the oscillation parameters, the damping coefficient, as shown in Fig. 8d and developing the tuned energy function. The initial values of Q is extracted from mode 1 and participation factors.



Fig. 9: Case F. Real-time dynamic performance of the power and control system (a) Area 2 Oscillation, (b) Control signals of Area 2.

# F. Case F. Unstable Case

Further, in order to show the efficiency of the proposed WADC during unstable disturbances, the fault duration of previous case study in real-time simulator has been increased to 135 ms. It can be seen that this condition has led to system instability with the presence of the local PSS acting alone or with the GPSS re-tuned based on inter-area modes of oscillation frequencies as shown in Fig. 9a. However, the proposed WADC has maintained the system stability. The respective controller contributions are shown in Fig. 9b. This case study demonstrates the effectiveness of the proposed technique in enhancement of the transient stability as the CCT or duration of the fault has been increased.

### VI. CONCLUSION

In this paper a new intelligent energy-based wide-area damping control design for improved power system transient stability is presented. The algorithm adapts the reinforcement learning to optimally solve for a control action policy through approximate dynamic programming. The cost function is defined to improve the inter-area oscillations and define transient energy function candidate. Furthermore, 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 IEEE 68-bus 16-machine system showed that the proposed method is able to guarantee the energy function in real-time and converge it to optimal operating point with higher damping.

#### REFERENCES

- P. Kundur et. al, "Definition and classification of power system stability ieee/cigre joint task force on stability terms and definitions," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1387–1401, Aug 2004.
- [2] S. McArthur et. al, "Multi-agent systems for power engineering applications—part i: Concepts, approaches, and technical challenges," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1743–1752, 2007.
- [3] I. Kamwa, R. Grondin, and Y. Hebert, "Wide-area measurement based stabilizing control of large power systems-a decentralized/hierarchical approach," *IEEE Trans. Power Syst.*, vol. 16, no. 1, pp. 136–153, 2001.
- [4] S. Khosravani, I. N. Moghaddam, A. Afshar, and M. Karrari, "Widearea measurement-based fault tolerant control of power system during sensor failure," *Electr. Pow. Syst. Res.*, vol. 137, pp. 66–75, 2016.

- [5] A. Darvishi and I. Dobson, "Threshold-based monitoring of multiple outages with pmu measurements of area angle," *IEEE Trans. on Power Syst.*, vol. 31, no. 3, pp. 2116–2124, 2016.
- [6] C. Dufour and J. Bélanger, "On the use of real-time simulation technology in smart grid research and development," *IEEE Trans. Ind. Appl*, vol. 50, no. 6, pp. 3963–3970, 2014.
- [7] S. Zarrabian, R. Belkacemi, and A. A. Babalola, "Reinforcement learning approach for congestion management and cascading failure prevention with experimental application," *Electr. Pow. Syst. Res.*, vol. 141, pp. 179–190, 2016.
- [8] J. Hazra, R. Reddi, K. Das, D. Seetharam, and A. Sinha, "Power grid transient stability prediction using wide area synchrophasor measurements," in *3rd IEEE PES Innovative Smart Grid Technologies Europe* (*ISGT Europe*), Oct 2012, pp. 1–8.
- [9] H.-D. Chiang, F. F. Wu, and P. P. Varaiya, "A bcu method for direct analysis of power system transient stability," *IEEE Transactions on Power Systems*, vol. 9, no. 3, pp. 1194–1208, 1994.
- [10] N. Amjady and S. Majedi, "Transient stability prediction by a hybrid intelligent system," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1275– 1283, Aug 2007.
- [11] I. Kamwa, R. Grondin et.al., "Time-varying contingency screening for dynamic security assessment using intelligent-systems techniques," *IEEE Trans. Power Syst.*, vol. 16, no. 3, pp. 526–536, Aug 2001.
- [12] J. Geeganage, U. Annakkage, T. Weekes, and B. Archer, "Application of energy-based power system features for dynamic security assessment," *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 1957–1965, 2015.
- [13] S.-M. Baek, J.-W. Park, and G. K. Venayagamoorthy, "Power system control with an embedded neural network in hybrid system modeling," *IEEE Trans. Ind. Appl*, vol. 44, no. 5, pp. 1458–1465, 2008.
- [14] D. Bertsekas and J. Tsitsiklis, "Neuro-dynamic programming: an overview," in *Proc. of the 34th IEEE Conf. on Decision and Control*, vol. 1, Dec 1995, pp. 560–564 vol.1.
- [15] D. Vrabie, O. Pastravanu, M. Abu-Khalaf, and F. L. Lewis, "Adaptive optimal control for continuous-time linear systems based on policy iteration," *Automatica*, vol. 45, no. 2, pp. 477–484, 2009.
- [16] R. Hadidi and B. Jeyasurya, "Reinforcement learning based real-time wide-area stabilizing control agents to enhance power system stability," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 489–497, March 2013.
- [17] W. Liu, G. K. Venayagamoorthy, and D. C. Wunsch, "A heuristicdynamic-programming-based power system stabilizer for a turbogenerator in a single-machine power system," *IEEE Trans. Ind. Appl*, vol. 41, no. 5, pp. 1377–1385, 2005.
- [18] D. Molina, J. Liang, R. Harley, and G. Venayagamoorthy, "Virtual generators: Simplified online power system representations for widearea damping control," in *Power and Energy Society General Meeting*, 2012 IEEE, 2012, pp. 1–8.
- [19] S. Mohagheghi, G. Venayagamoorthy, and R. Harley, "Optimal wide area controller and state predictor for a power system," *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 693–705, 2007.
- [20] R. Yousefian and S. Kamalasadan, "Design and real-time implementation of optimal power system wide-area system-centric controller based on temporal difference learning," *IEEE Trans. Ind. Appl*, vol. 52, no. 1, pp. 395–406, 2016.
- [21] A. Heydari and S. N. Balakrishnan, "Global optimality of approximate dynamic programming and its use in non-convex function minimization," *Applied Soft Computing*, vol. 24, no. 1, pp. 291–303, 2014.
- [22] R. Yousefian, A. Sahami, and S. Kamalasadan, "Hybrid energy function based real-time optimal wide-area transient stability controller for power system stability," in *Industry Applications Society Annual Meeting*, 2015 IEEE, Oct 2015, pp. 1–8.
- [23] J. Chow and P. Kokotovic, "Time scale modeling of sparse dynamic networks," *IEEE Trans. Autom. Control*, vol. 30, no. 8, pp. 714–722, Aug 1985.
- [24] M. L. Ourari, L.-A. Dessaint, and V.-Q. Do, "Dynamic equivalent modeling of large power systems using structure preservation technique," *IEEE Trans. Power Syst.*, vol. 21, no. 3, pp. 1284–1295, 2006.
- [25] M. J. Basler and R. C. Schaefer, "Understanding power-system stability," *IEEE Trans. Ind. Appl*, vol. 44, no. 2, pp. 463–474, 2008.
- [26] J. Machowski, S. Robak, J. Bialek, J. Bumby, and N. Abi-Samra, "Decentralized stability-enhancing control of synchronous generator,"

IEEE Transactions on Power Systems, vol. 15, no. 4, pp. 1336–1344, 2000.

- [27] S. Fabri and V. Kadirkamanathan, Functional adaptive control: an intelligent systems approach. Springer Science & Business Media, 2012.
- [28] D. Ruiz-Vega, A. Messina, and M. Pavella, "Online assessment and control of transient oscillations damping," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1038–1047, May 2004.
- [29] S. Nabavi, J. Zhang, and A. Chakrabortty, "Distributed optimization algorithms for wide-area oscillation monitoring in power systems using interregional pmu-pdc architectures," *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2529–2538, Sept 2015.
- [30] IEEE 68 bus system benchmark model. [Online]. Available: http://www.sel.eesc.usp.br/ieee/
- [31] W. Yao, L. Jiang, J. Wen, Q. Wu, and S. Cheng, "Wide-area damping controller for power system interarea oscillations: A networked predictive control approach," *IEEE Trans. Control Syst. Technol.*, vol. 23, no. 1, pp. 27–36, 2015.
- [32] R. Yousefian and S. Kamalasadan, "Energy function inspired value priority based global wide-area control of power grid," *IEEE Trans.* on Smart Grid, vol. PP, no. 99, pp. 1–1, 2016.
- [33] Hypersim. [Online]. Available: http://www.opal-rt.com/new-product/ hypersim-power-system-real-time-digital-simulator



**R. Yousefian** (SM' 08) received his BS degree from the Amirkabir University of Technology in 2008 and his MS degree from the University of Tehran in 2011. He is currently working on his PhD degree in the department of Electrical and Computer Engineering of University of North Carolina at Charlotte. His research interests include Smart grid, Intelligent and Autonomous control, Power system dynamics, Stability and Control.



**A. Sahami** (SM' 11) received his BSc in electrical engineering at Shiraz University of Technology in 2010 and his M.Sc. for Amirkabir University of Technology in 2013 working on software development and realtime simulation for dynamic studies of power system. He is currently working on his PhD degree in the department of electrical and computer engineering at the University of North Carolina at Charlotte. His research interests are power system stability with main focus being on transient stability using direct methods.



**S. Kamalasadan** (M' 05) received his Ph.D. in Electrical Engineering from the University of Toledo, Ohio in 2004, M.Eng in Electrical Power Systems Management, from the Asian Institute of Technology, Bangkok Thailand in 1999 and B Tech. degree in Electrical and Electronics from the University of Calicut, India in 1991. He is currently working as an Associate Professor at the department of electrical and computer engineering at the University of North Carolina at Charlotte. He has won several awards including the NSF CAREER award.

His research interests include Intelligent and Optimization and Control of Power System, Smart Grid and Micro grid.