Artificial Intelligence Applications in Power Systems

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What is Artificial Intelligence?

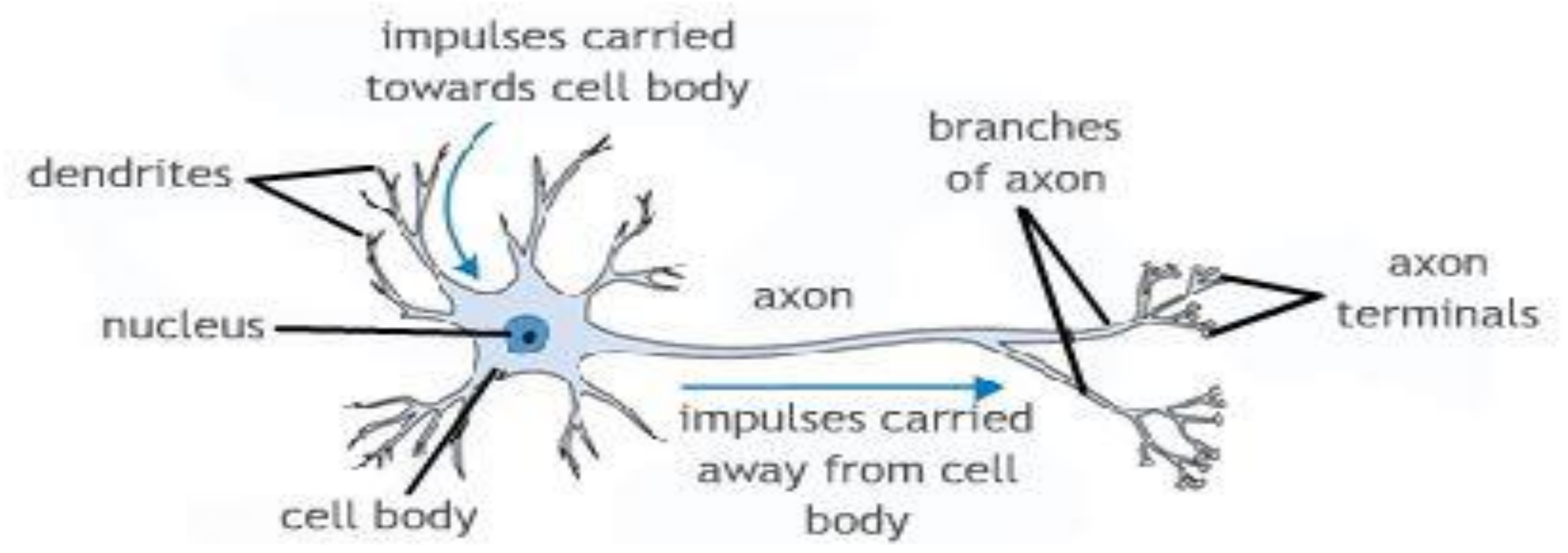
Artificial Intelligence (AI) has recently emerged as a science even though it may still be considered in its early stages of development.
Depending on the goals and methods employed in research, its definition varies. As a broad description, it may be described as the science of making machines do things that would require intelligence if done by humans.

AI applications are now being considered in a very wide variety of disciplines, ranging from humanities to natural and applied sciences. In the context of power systems, application of artificial neural networks (ANNs) and fuzzy logic is commonly referred to in the literature as AI applications in power systems.

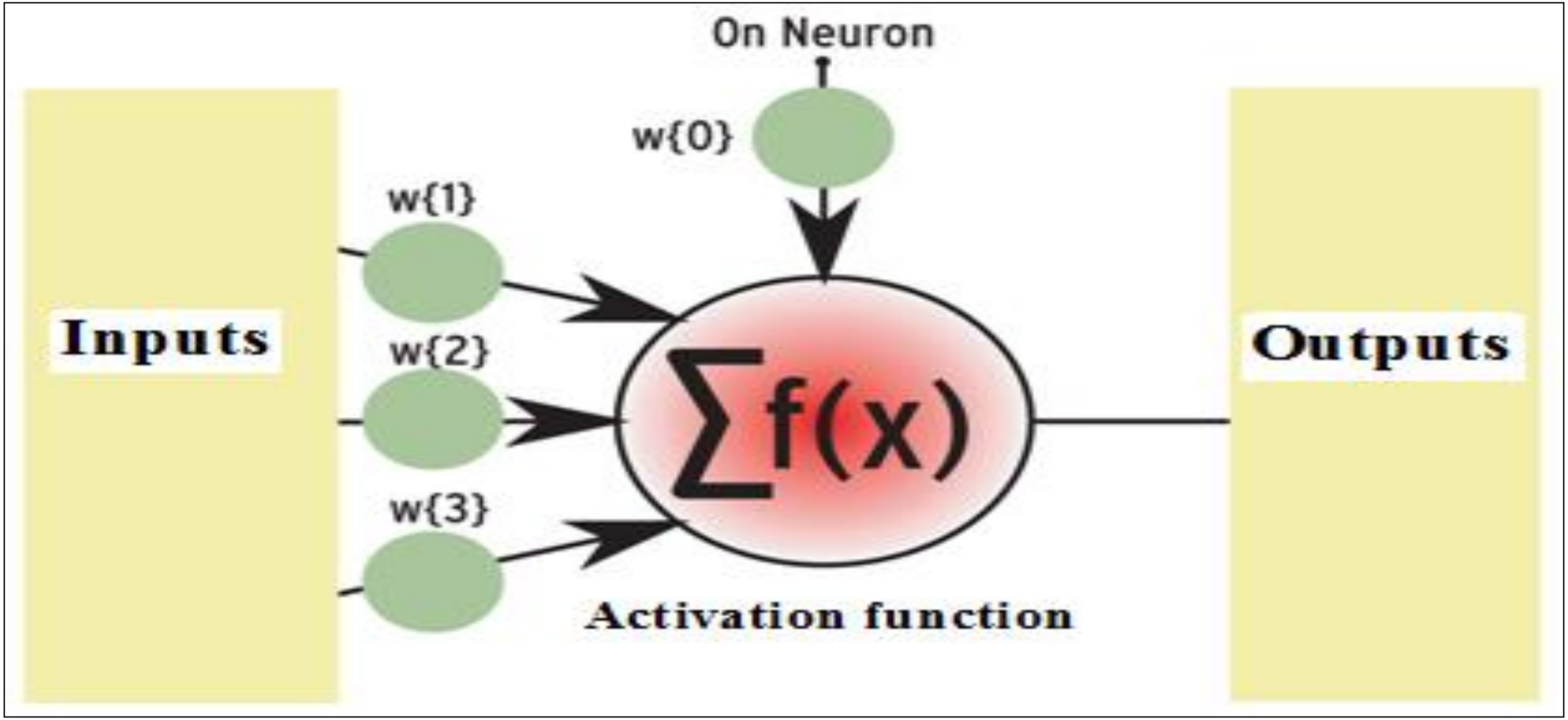
Over the past 25 years or so, feasibility of the application of AI for a variety of topics in power systems has been explored by a number of investigators. Topics explored vary from load forecast to real-time control and protection, and even maintenance.

Artificial Neural Networks

Natural Nerve Cell



Artificial Nerve Cell



Networks Based on Artificial Nerve Cell Model

- Multi-layer feed-forward perceptron
- Recurrent
- Radial basis function
- Adaline
- Bayesian
- Hopfield
- Boltzman
- Kohonen
- Generalized Regression network

Types of Neuron Models

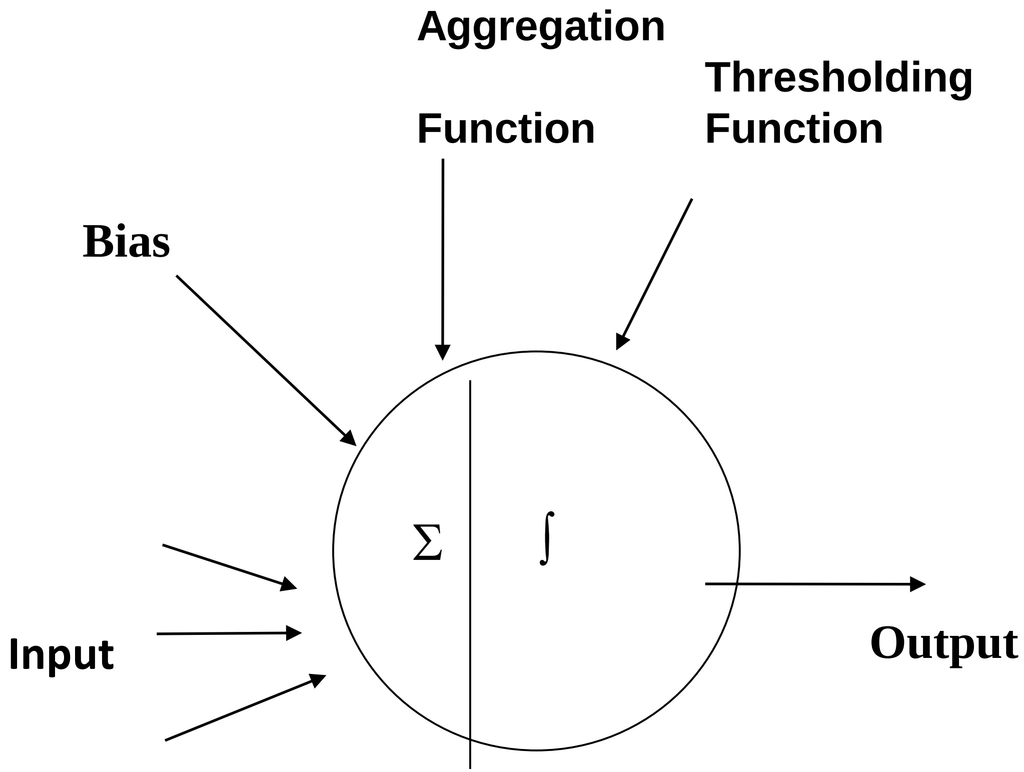
- Artificial Neuron Cell Model
- Multiplicative neuron

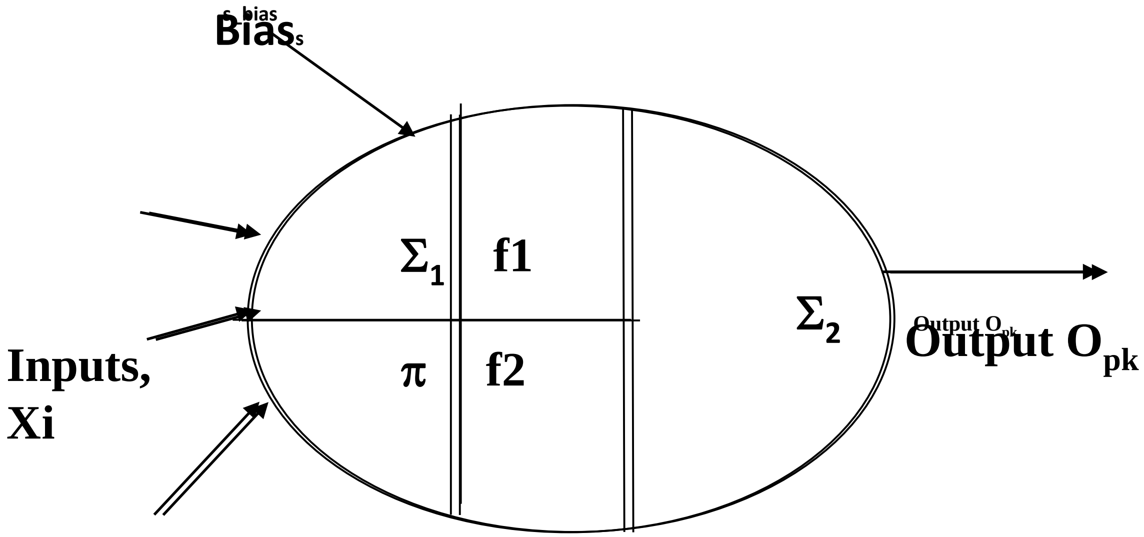
Reacts to product of activation of pairs of synapses

- Generalized neuron

Contains both summation and aggregation functions with sigmoid and Gaussian activation functions

Simple and Generalized Neuron Models





DEFERENT ANN MODELS

Σ– ANN
(Conventional ANN)

Input layer	Σ –hidden layer	Σ –output layer

Π – ANN

Input layer	Π–hidden layer	Π –output layer

Σ –Π –ANN

Input layer	Σ –hidden layer	Π –output layer

Π –Σ –ANN

Input layer	Π–hidden layer	Σ–output layer

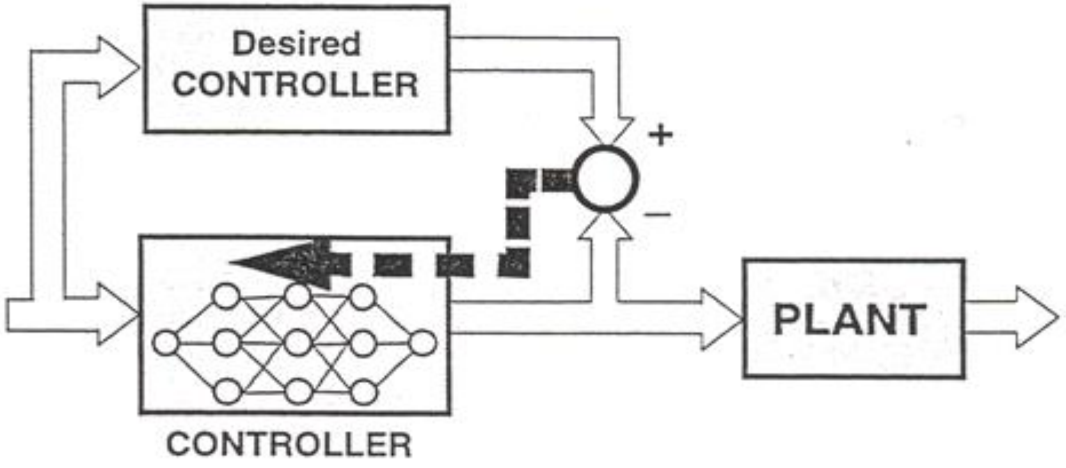
Training of Neural Networks

Neural networks need to be trained. Based on the type of network, it may be:

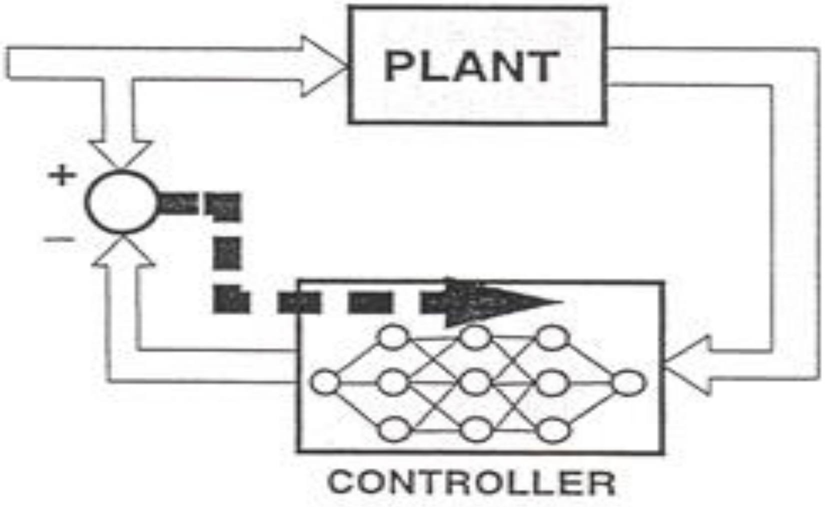
- Supervised learning
- Unsupervised learning
- Competitive

Although most networks are trained off-line using available data, in some cases the weights can be up-dated on-line in real-time to track the system operating conditions.

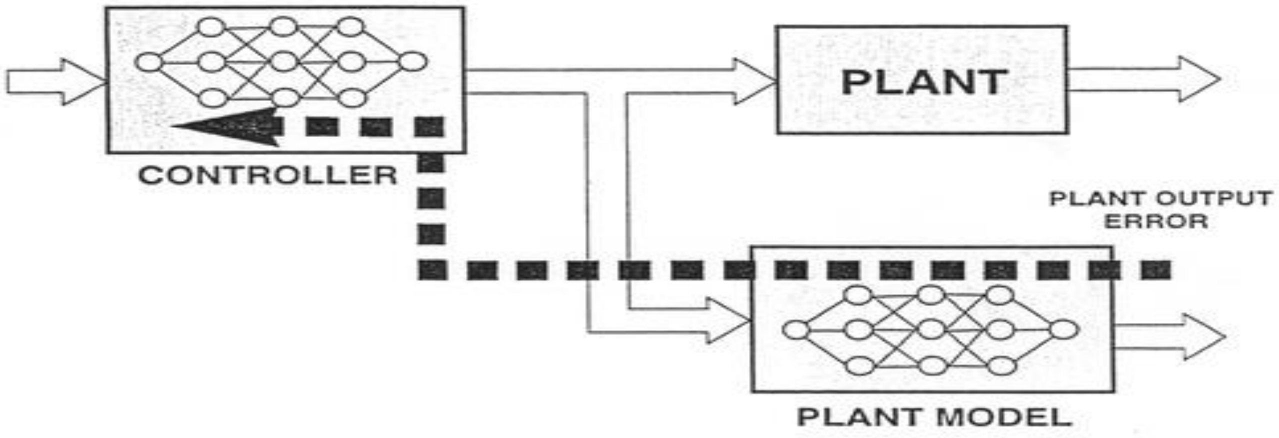
Neural Network Controllers



Copying an existing controller with a network.



Inverse plant modeling using a network.



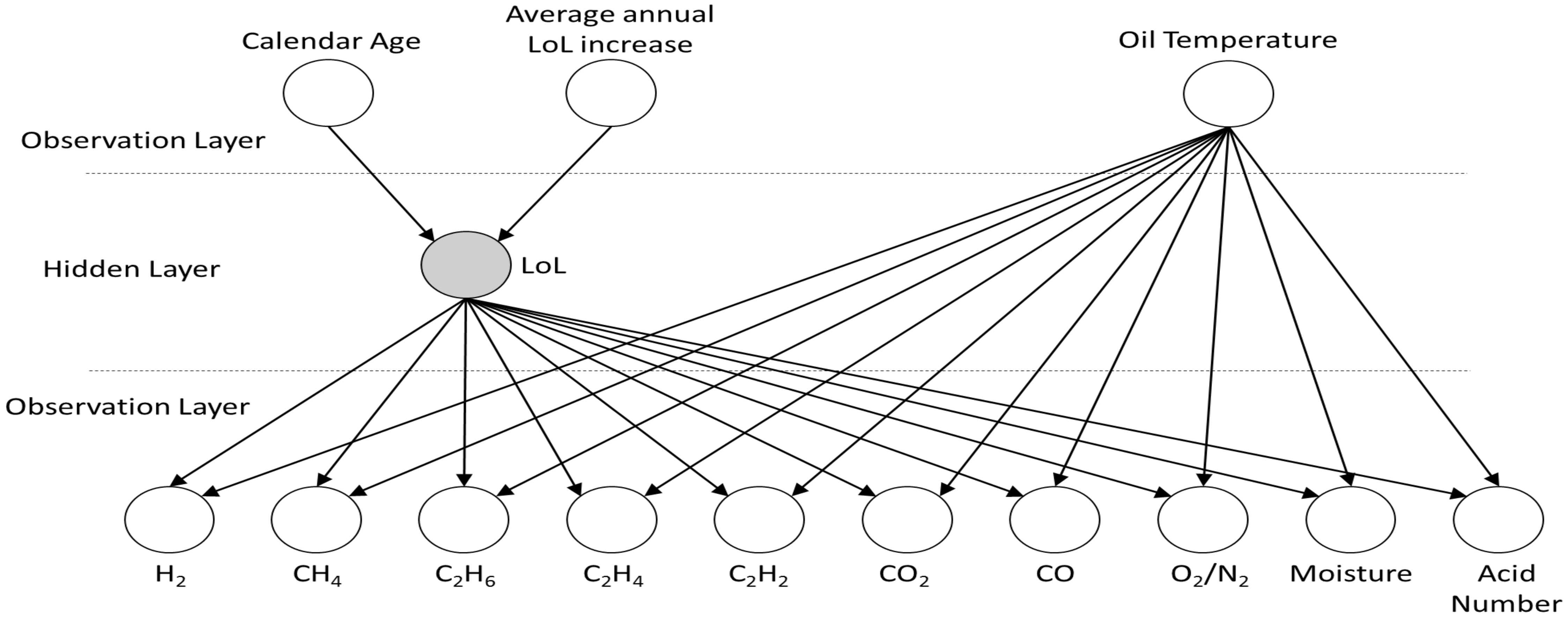
Back propagating through a forward model of the plant.

Bayesian Networks

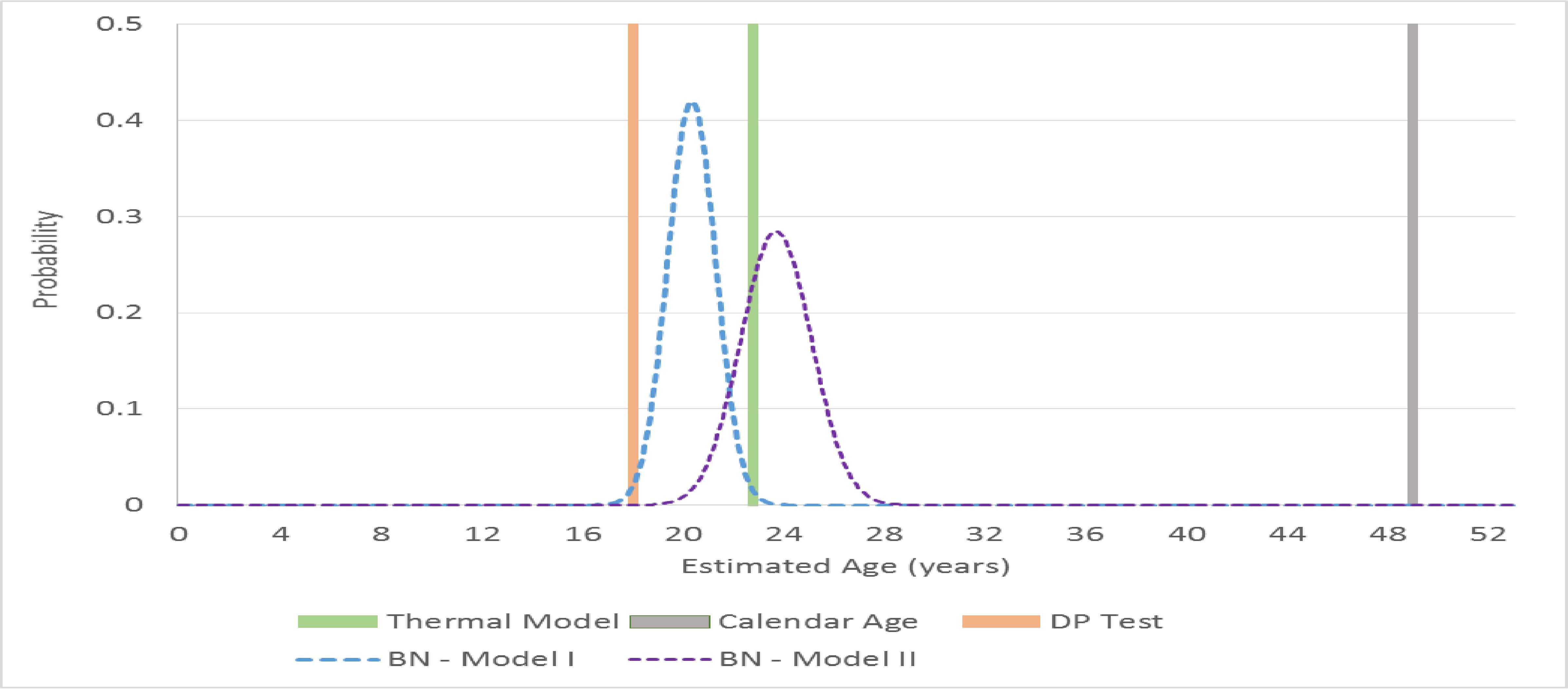
A Bayesian network (BN), also known as a Bayesian belief network, is a graphical model for probabilistic relationships among a set of variables. They have a qualitative component represented by the network structure and a quantitative component represented by the assignment of the conditional probability (CP) distributions to the nodes of the network.

BNs can learn from observations. Learning of BNs can be parameter learning and structure learning. With parameter learning, the structure of the BN is given and only the CP parameters are learned. With structure learning, the BN structure itself is learned. Bayesian learning calculates the probability of each of the hypotheses given the data.

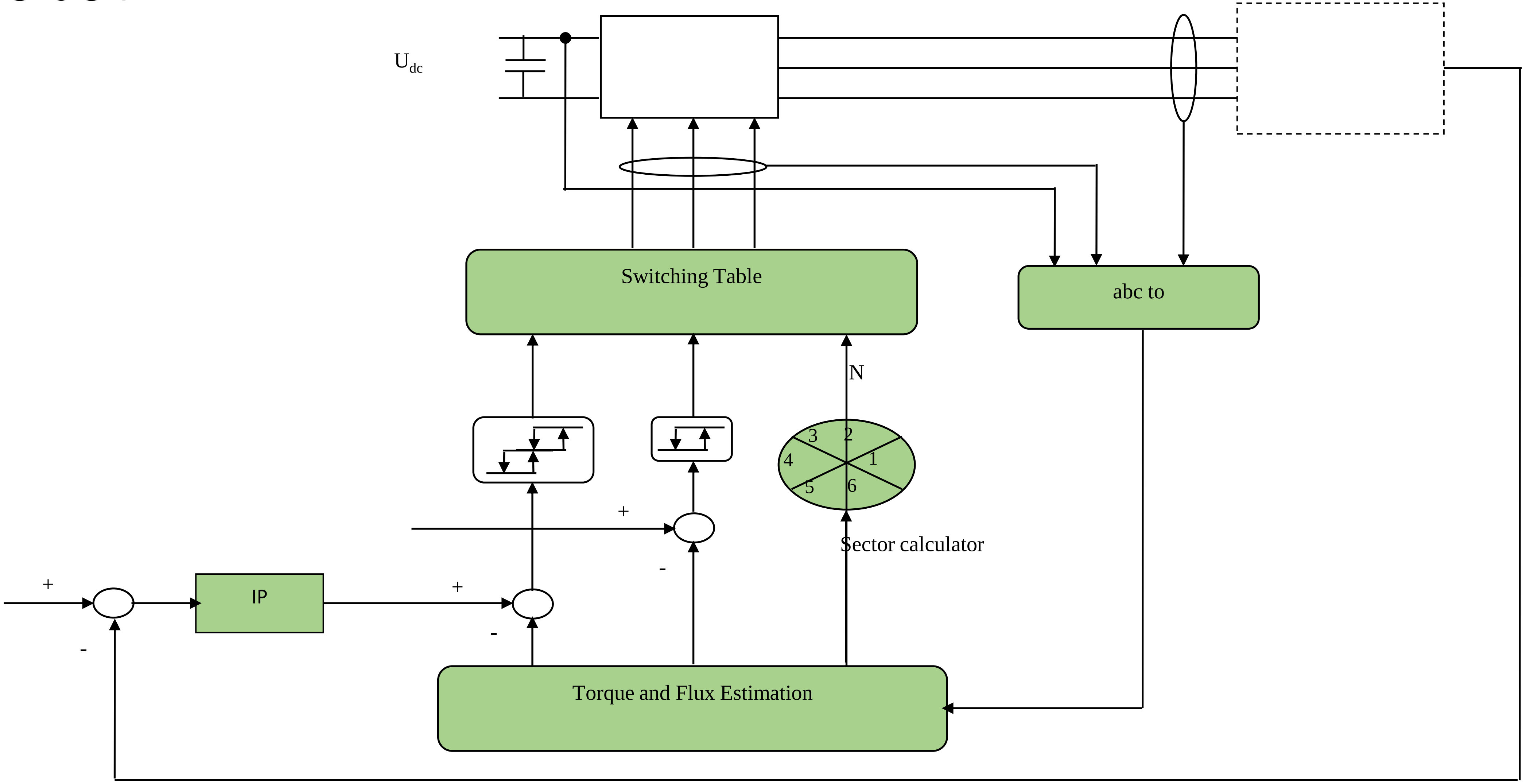
Insulation Deterioration Estimation of a Transformer Using a Bayesian Network



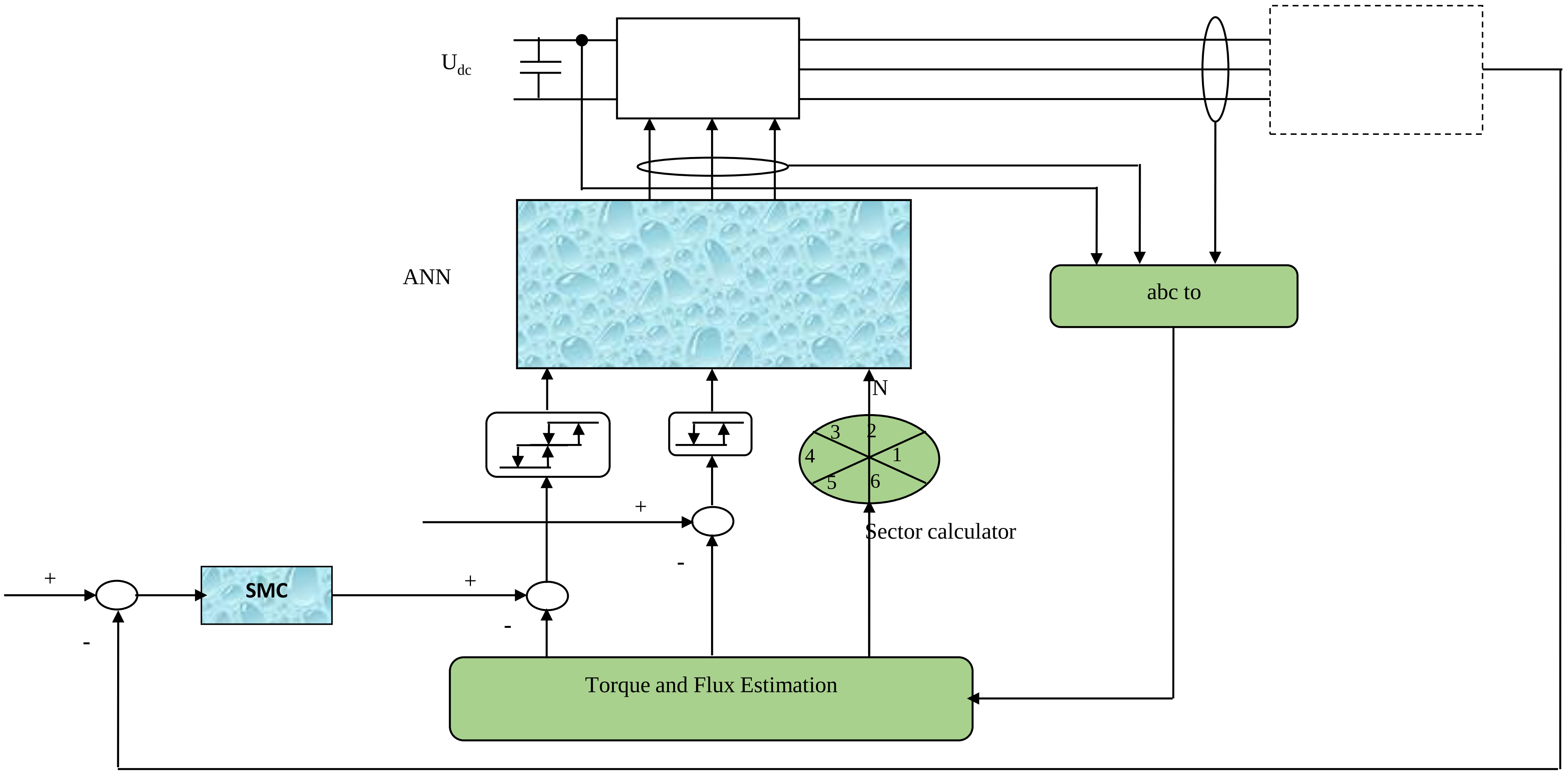
Insulation LoL estimation by BN versus other methods for unit #64



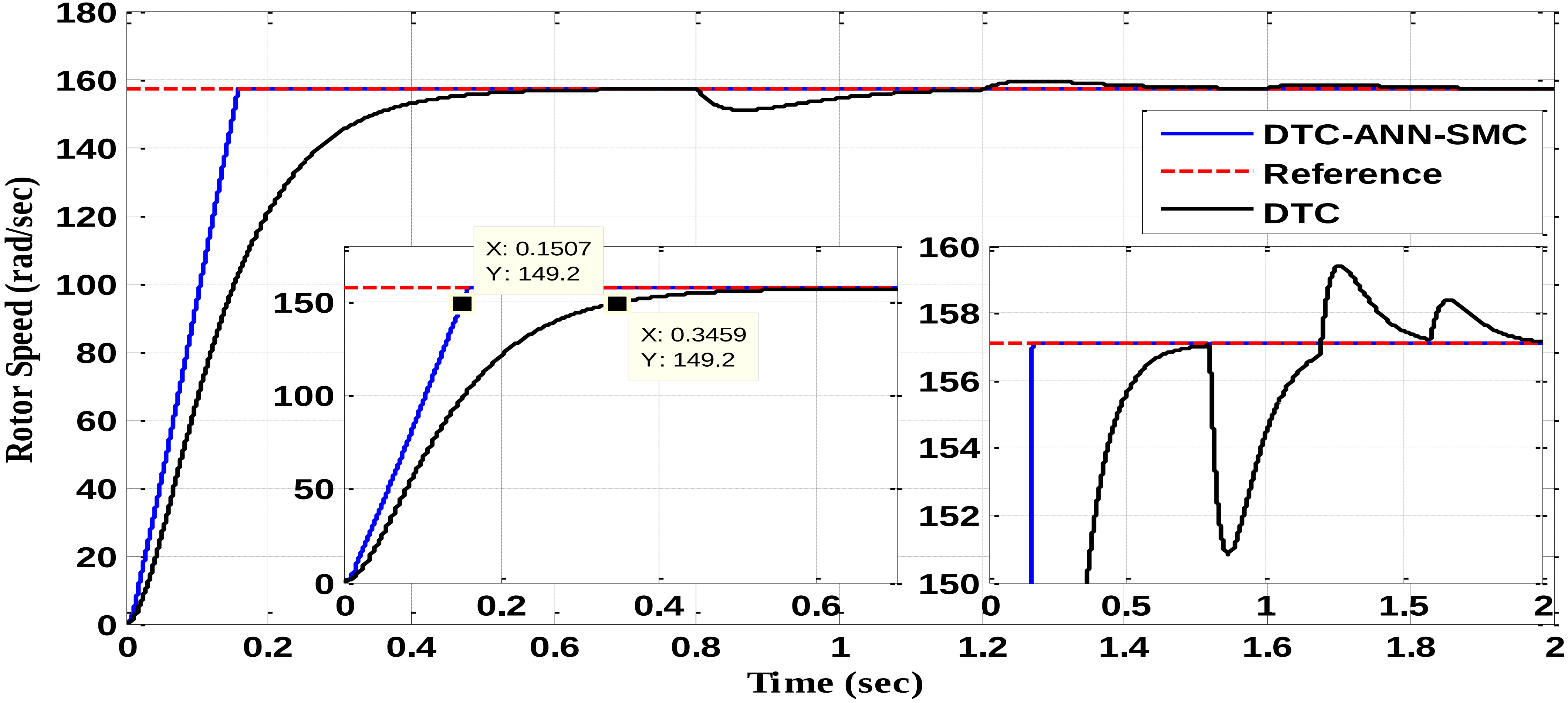
Classical Direct Torque Control of an Induction Motor



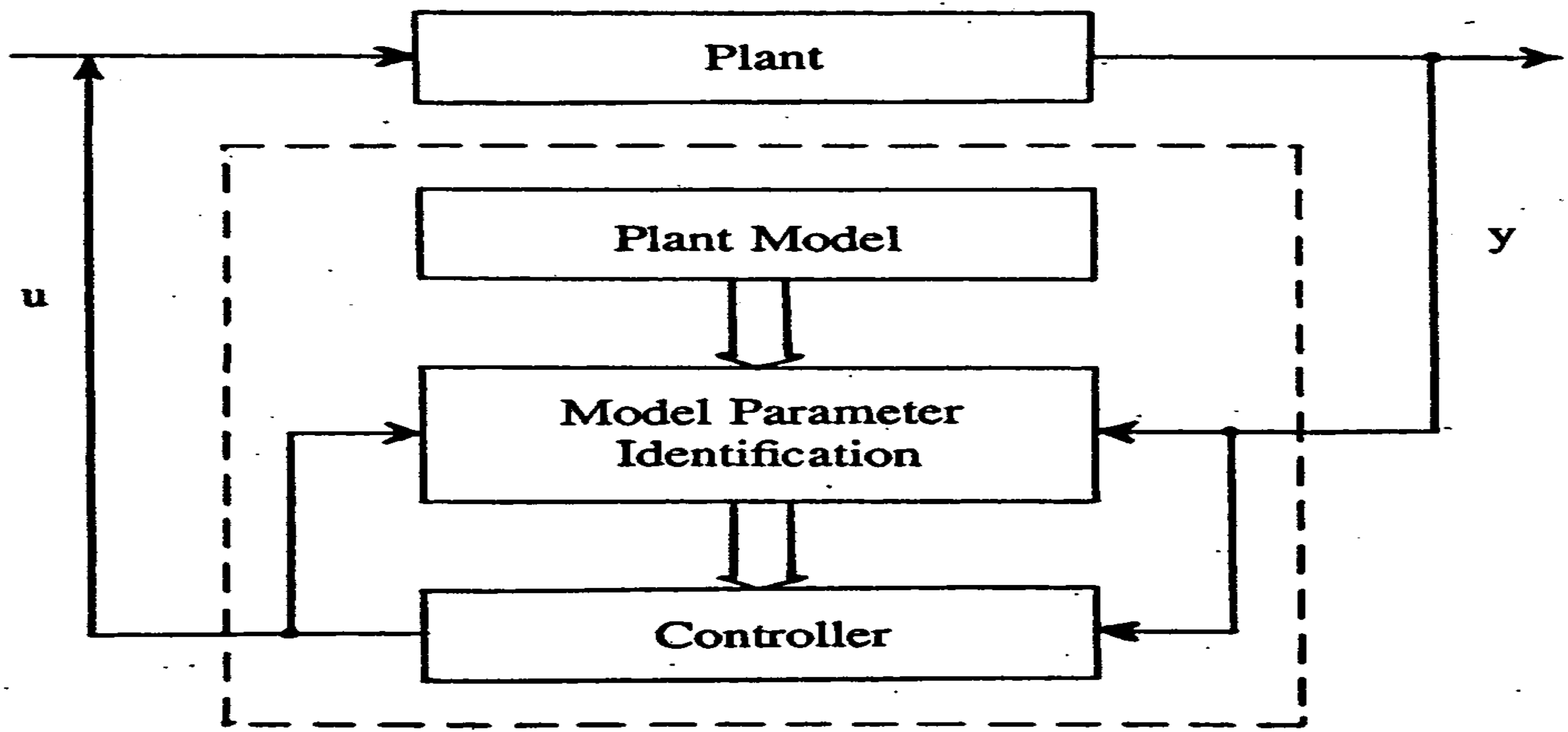
ANN Based DTC of an Induction Motor



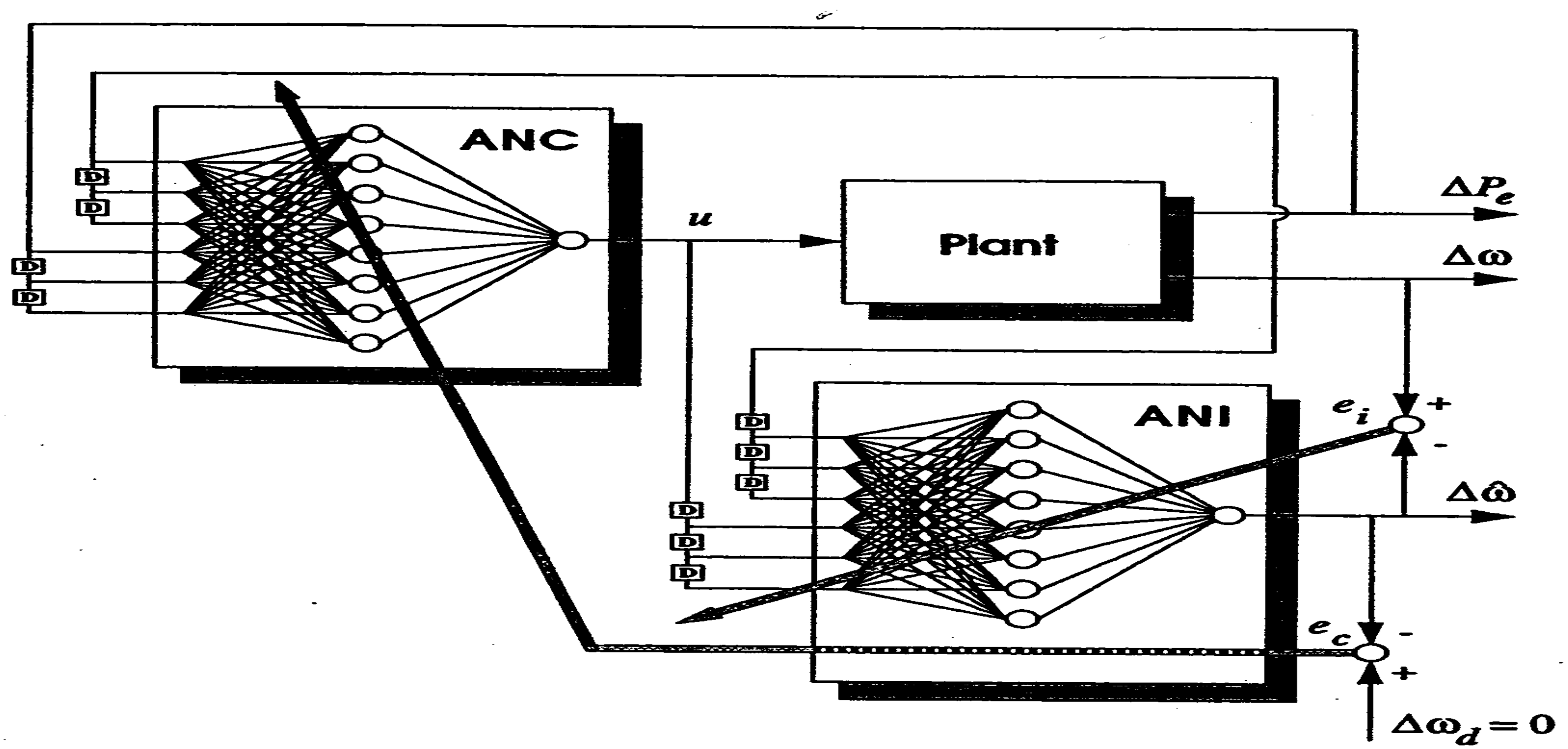
PI-DTC versus ANN-SMC-DTC



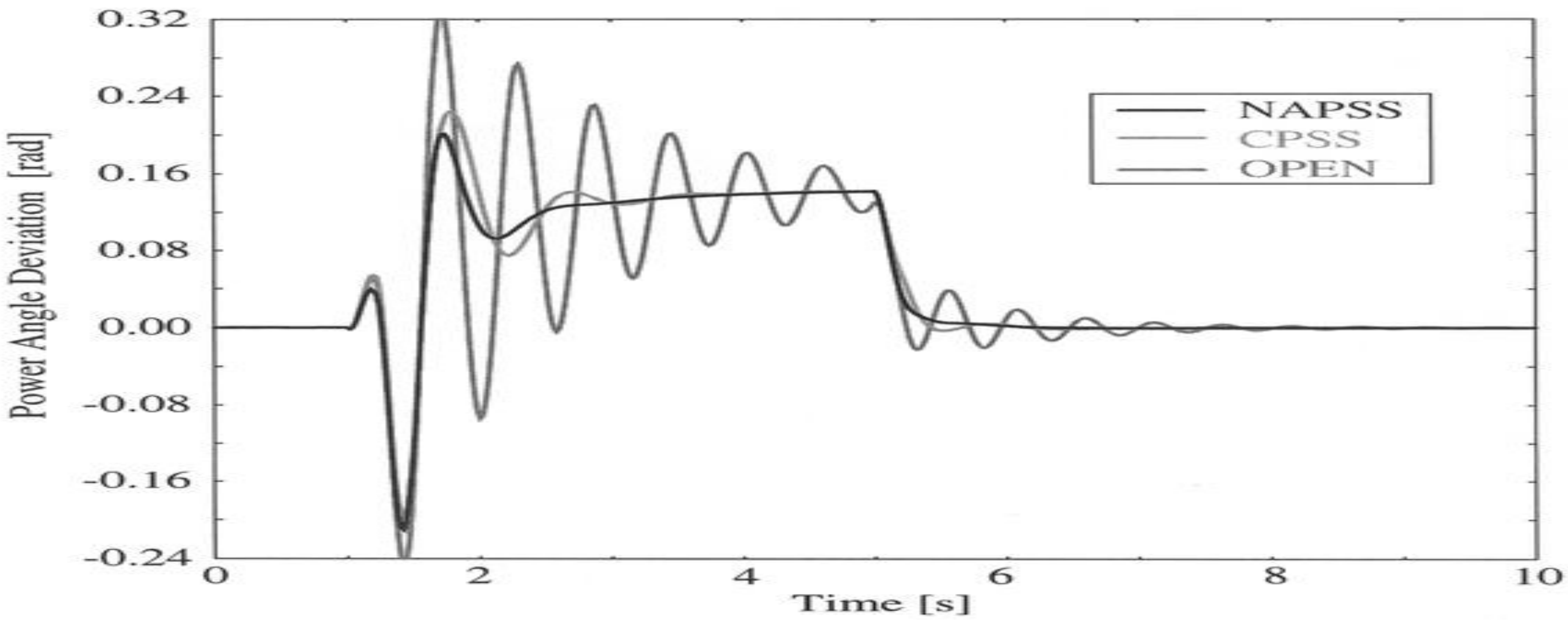
Block Diagram of an Adaptive Controller



Controller Structure with MLFF NNs



Neuro-Adaptive PSS



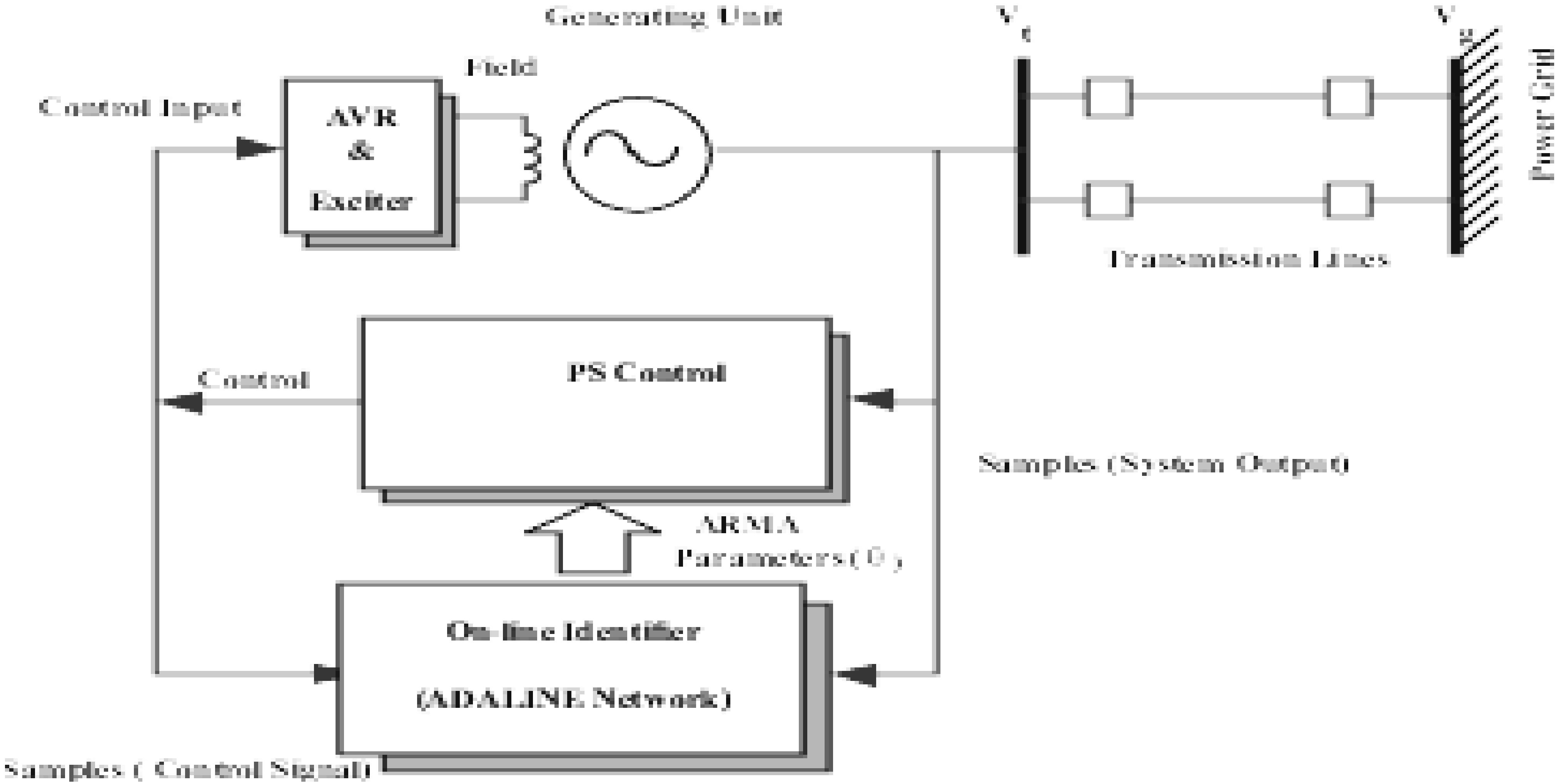
Response to a three phase to ground fault, p=0.7 pu, pf=0.62

Table 1:Dynamic Stability Margin* for Different Stabilizers.

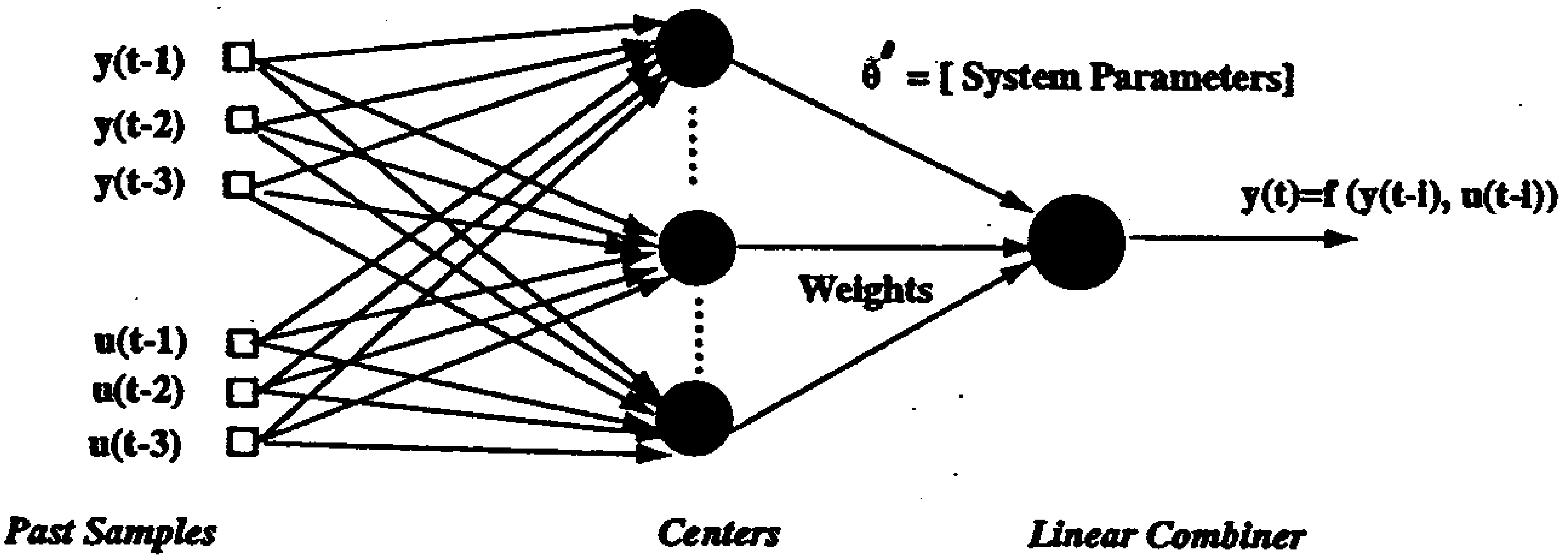
	OPEN	CPSS	NAPSS
Maximum Power	2.65 pu	3.35 pu	3.60 pu
Maximum Rotor Angle	1.55 rad	2.14 rad	2.36 rad

* Dynamic Stability Margin is defined as the maximum power output at which the generator loses synchronism while input torque reference is gradually increased

ADALINE Network as an Identifier



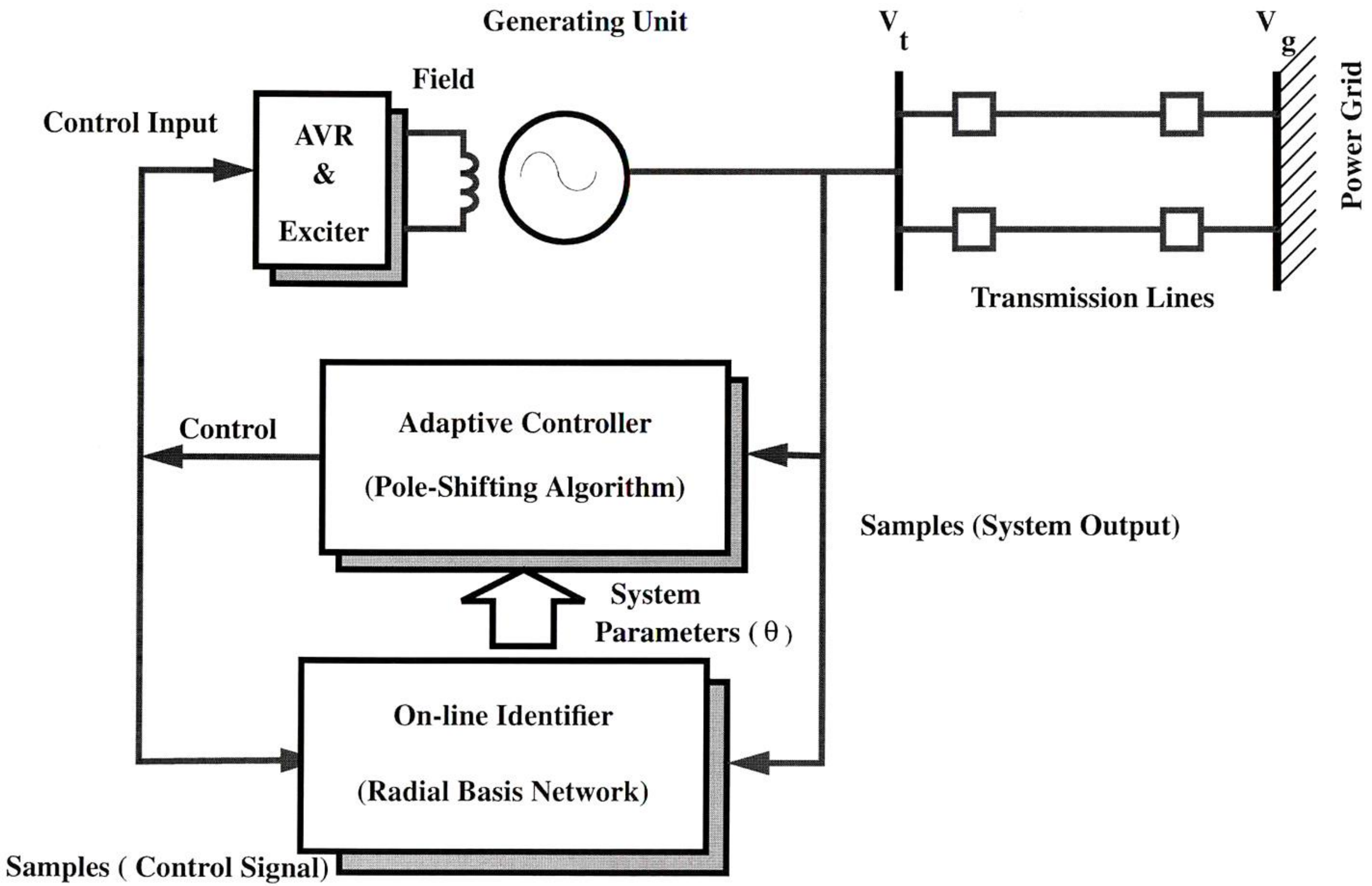
Radial Basis Function Network



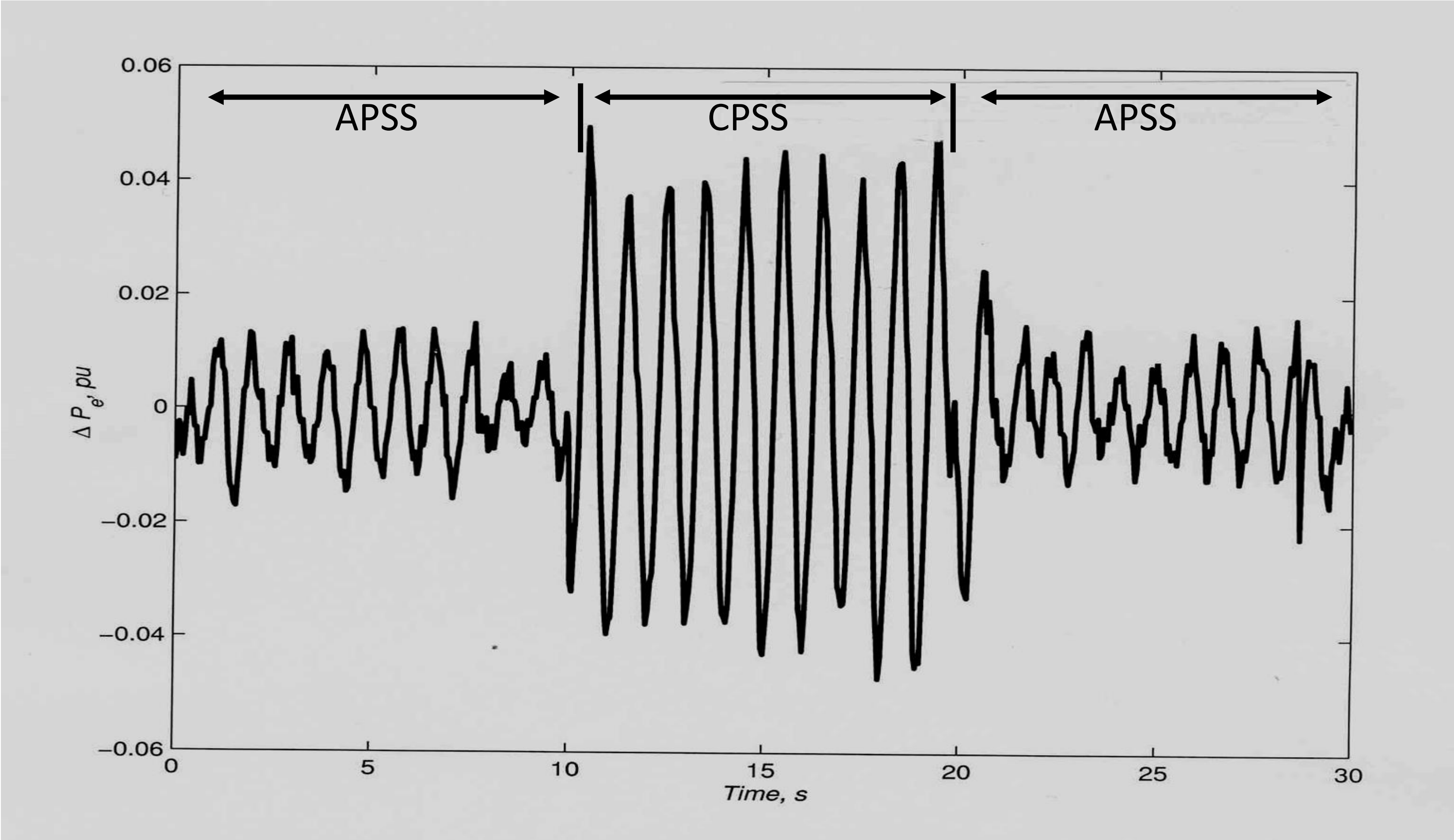
Centers : Adjusted Using n-means Clustering (Off-line)

Weights: Adjusted Using Recursive Least-Squares Algorithm (On-line)

RBF-Identifier & Pole-Shifting Controller



Stability Margin Test



Experimental Power System Model

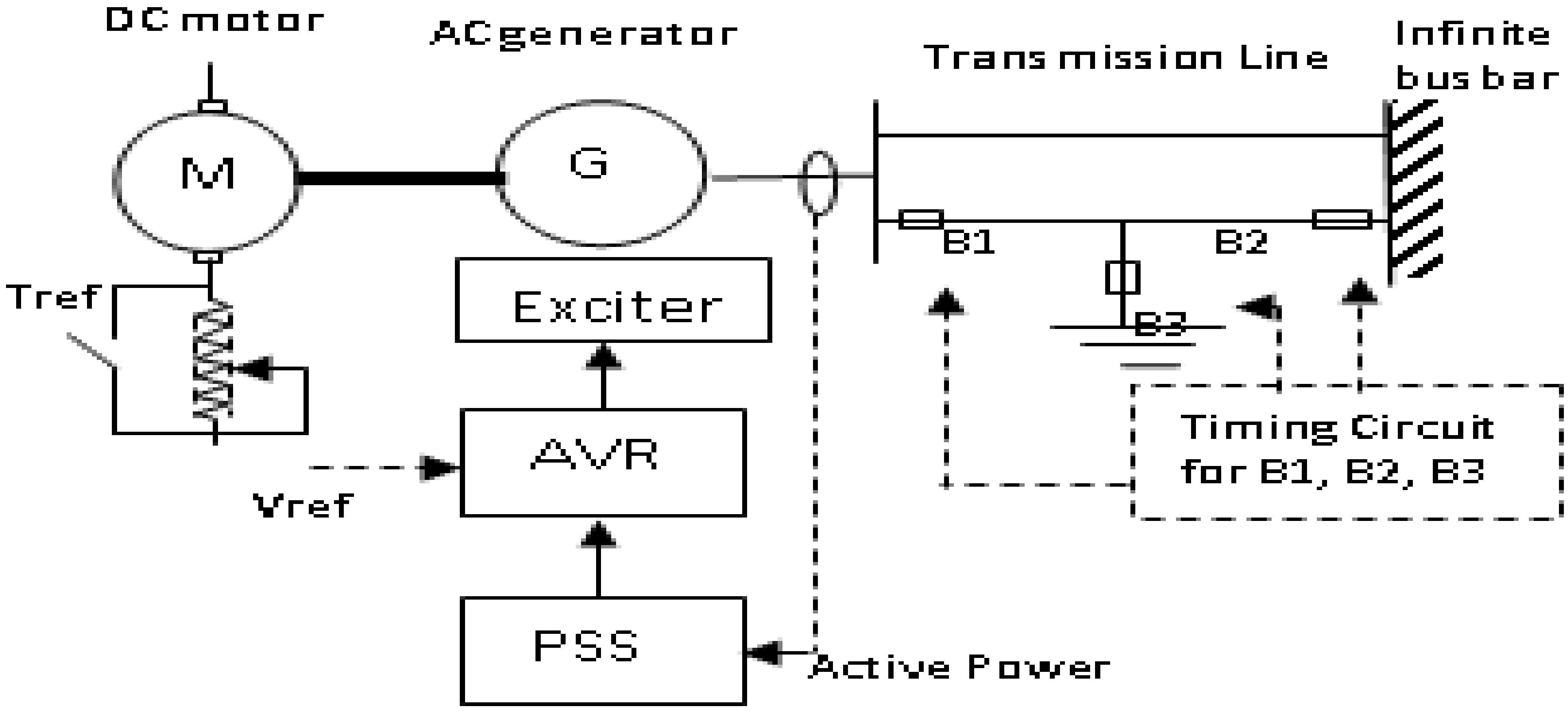
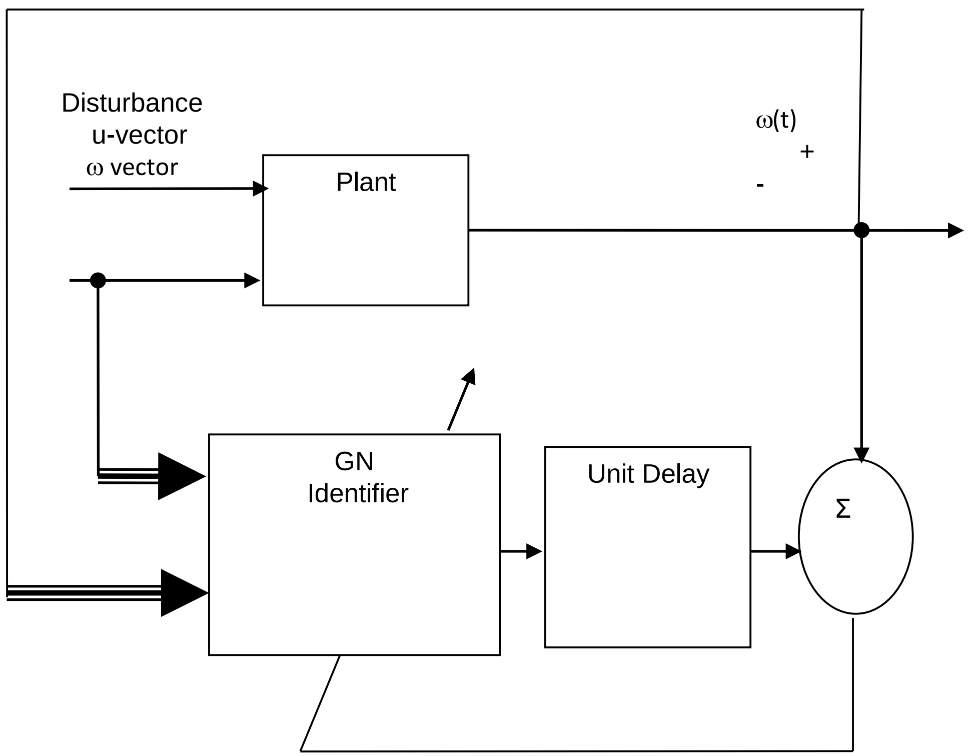
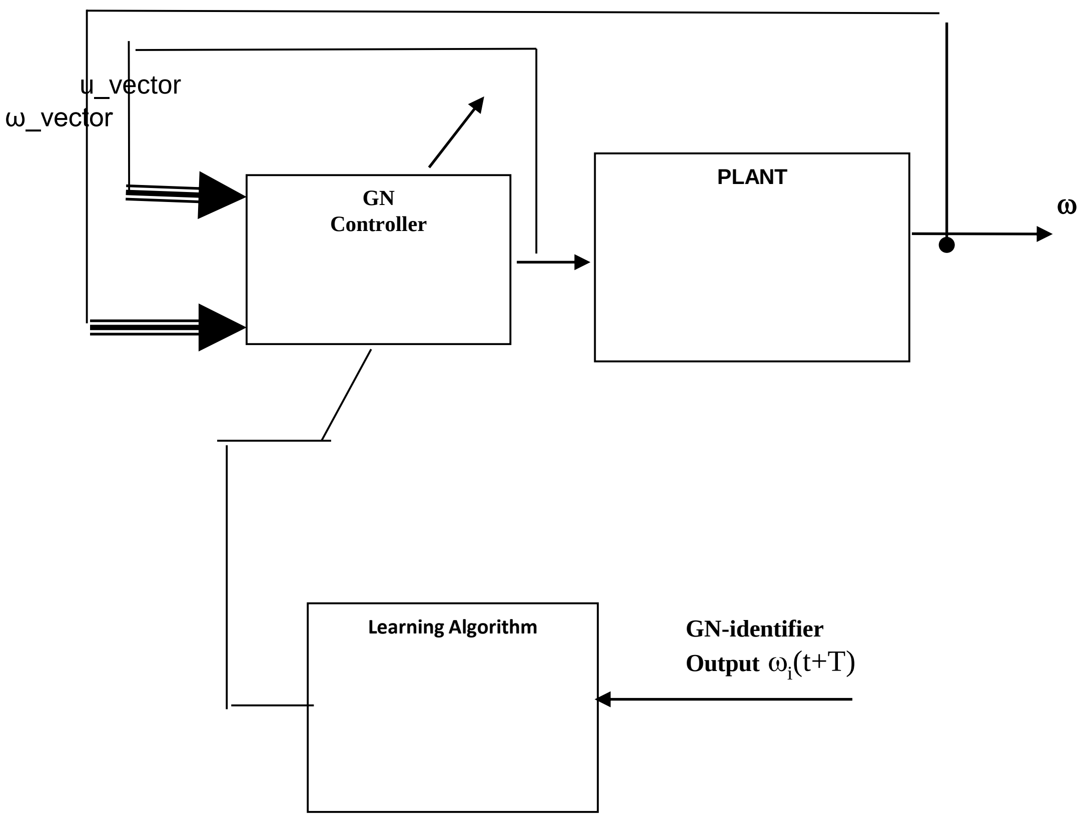


Fig. 6 Experimental setup for Laboratory Power System model

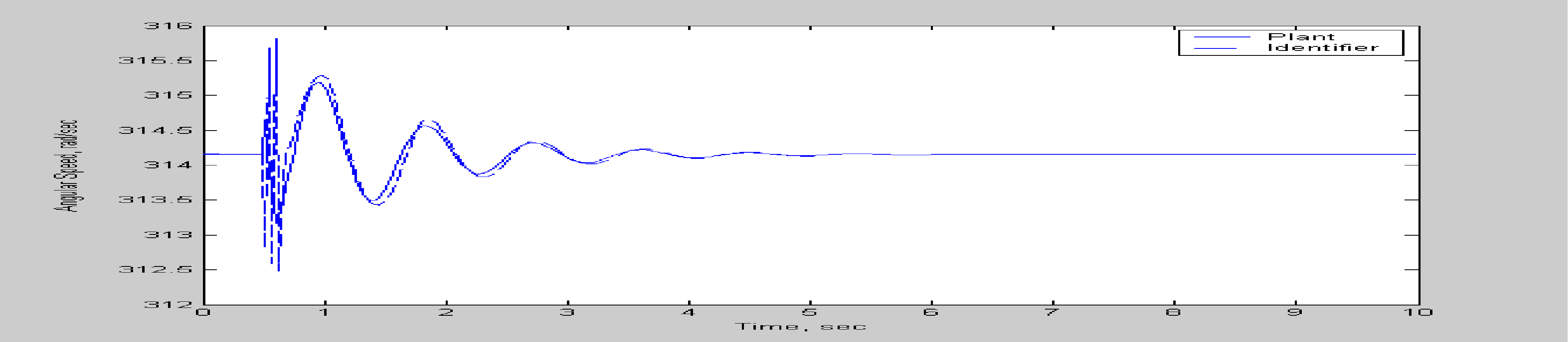
Identifier



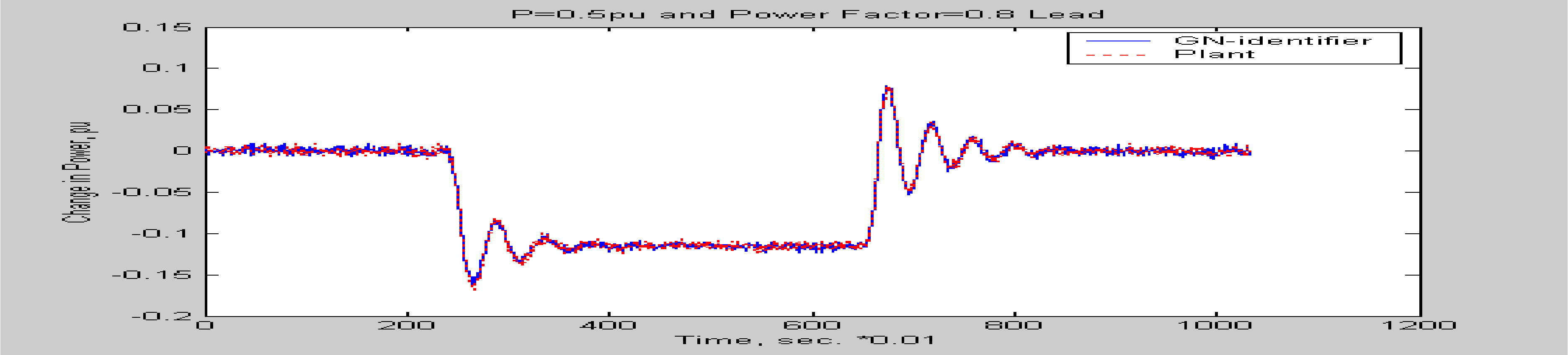
Controller



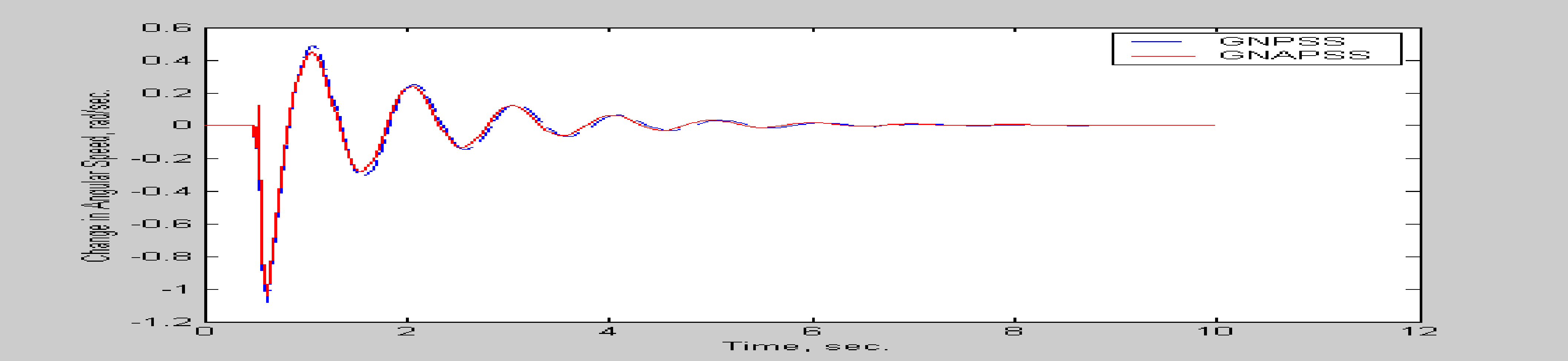
Performance of GN identifier



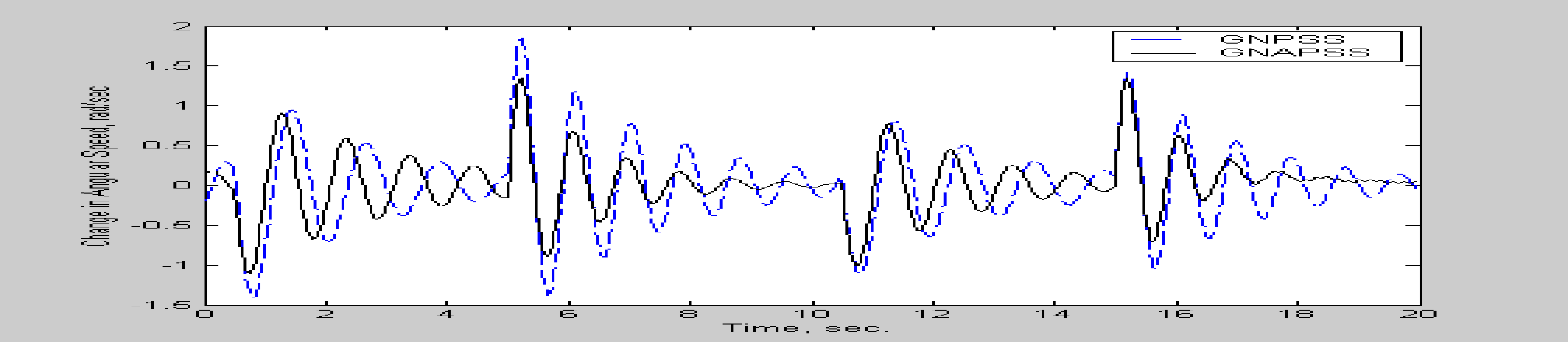
Results of GN identification for a 3-Phase to Ground fault at generator bus for 100 ms at P=0.7, Q=0.3 (lag).



Experimental Results of GN identification under 23 % step change in torque reference and trained on-line.



Performance of GNPSS and GNAPSS under three phase to ground fault for 100ms at the middle of one line in a double circuit system at P=0.7pu and Q=0.3 pu (lag) .

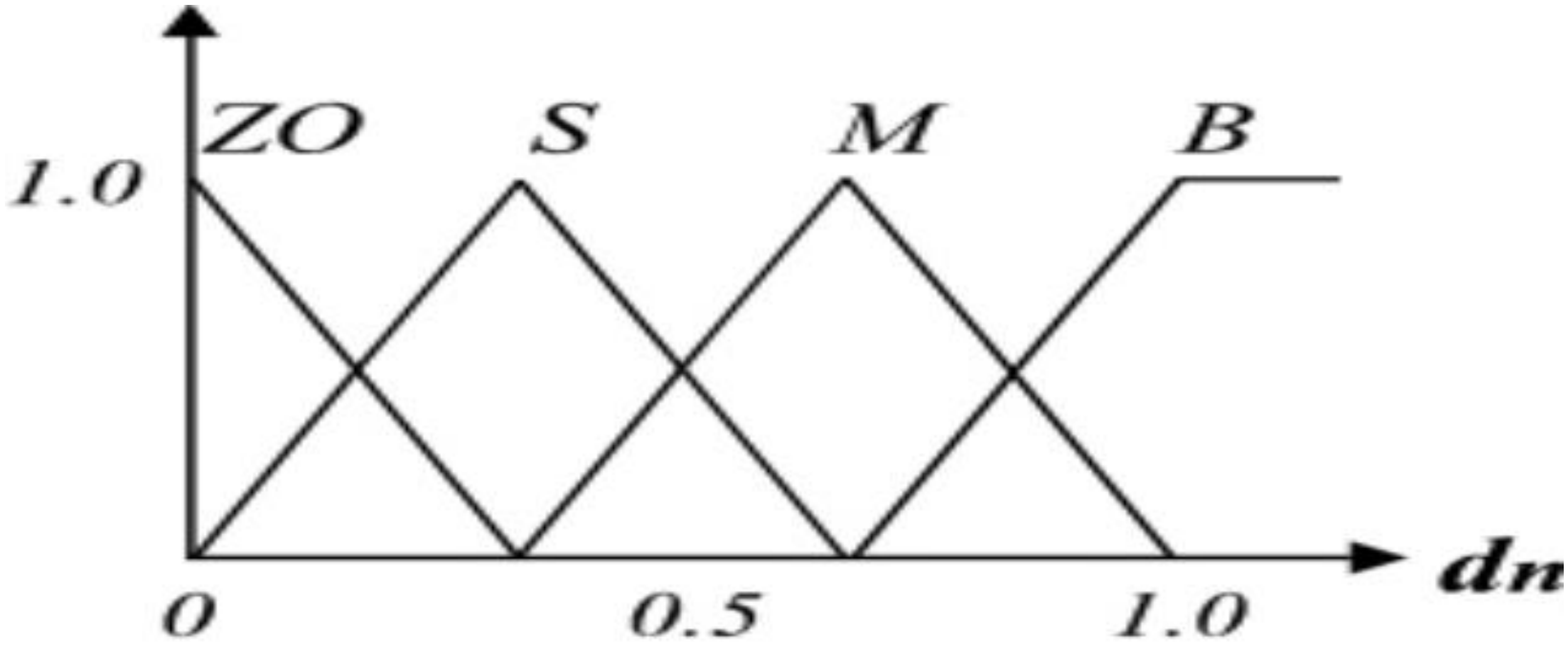


Performance of GNPSS and GN based adaptive PSS when one line is removed at 0.5 sec. and re-energized at 5.5 sec and then again same line is removed at 10.5 sec. and re-energized at 15.5 sec. at P=0.8 pu and Q=0.4 pu (leading).

Fuzzy Logic

General Concept

Fuzzy Logic Membership Functions



Examples of Membership Functions distributions

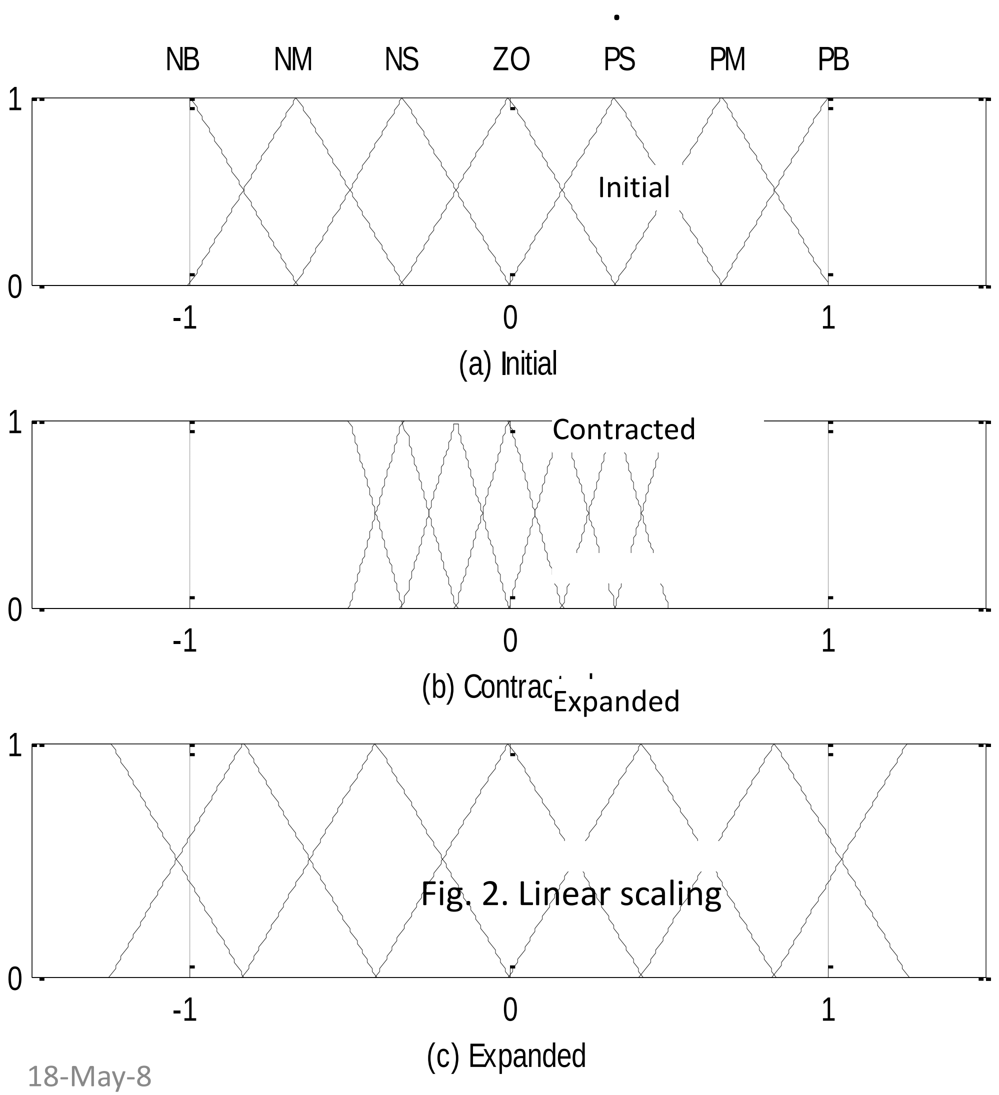


Fig. 2. Linear scaling

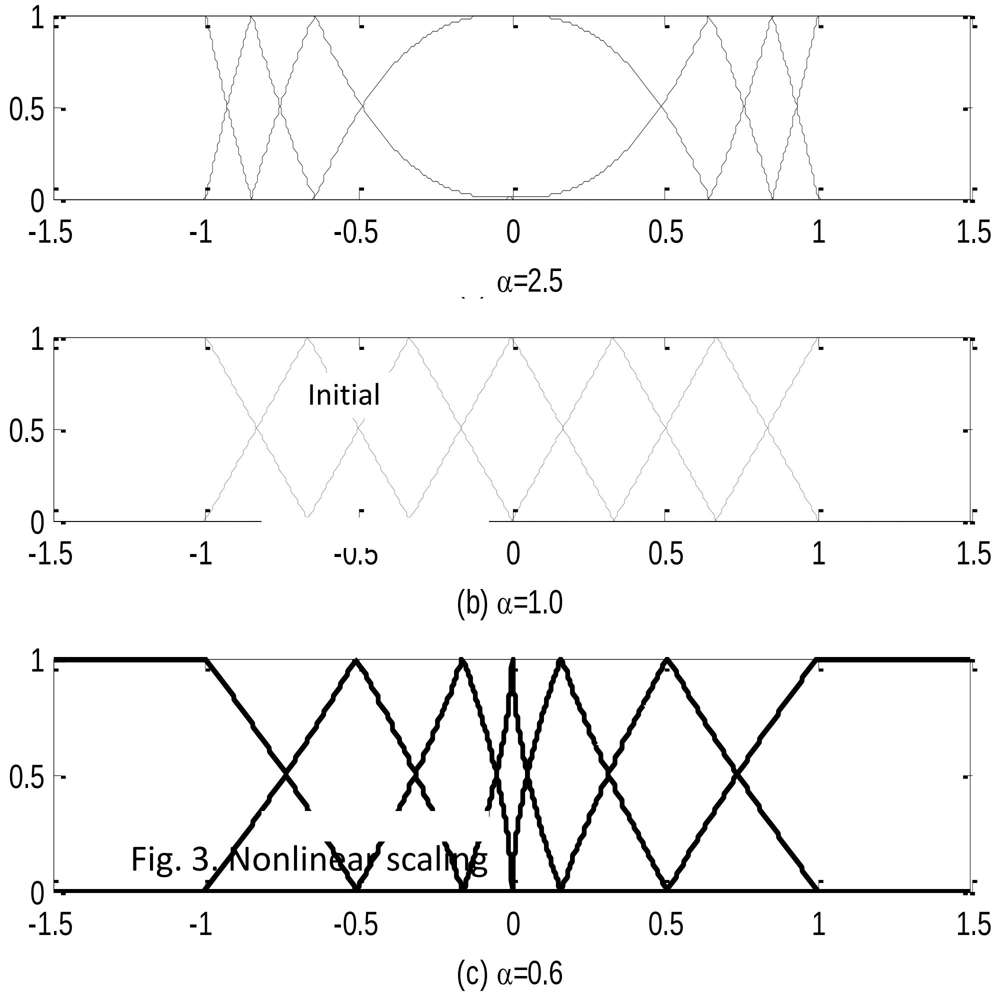
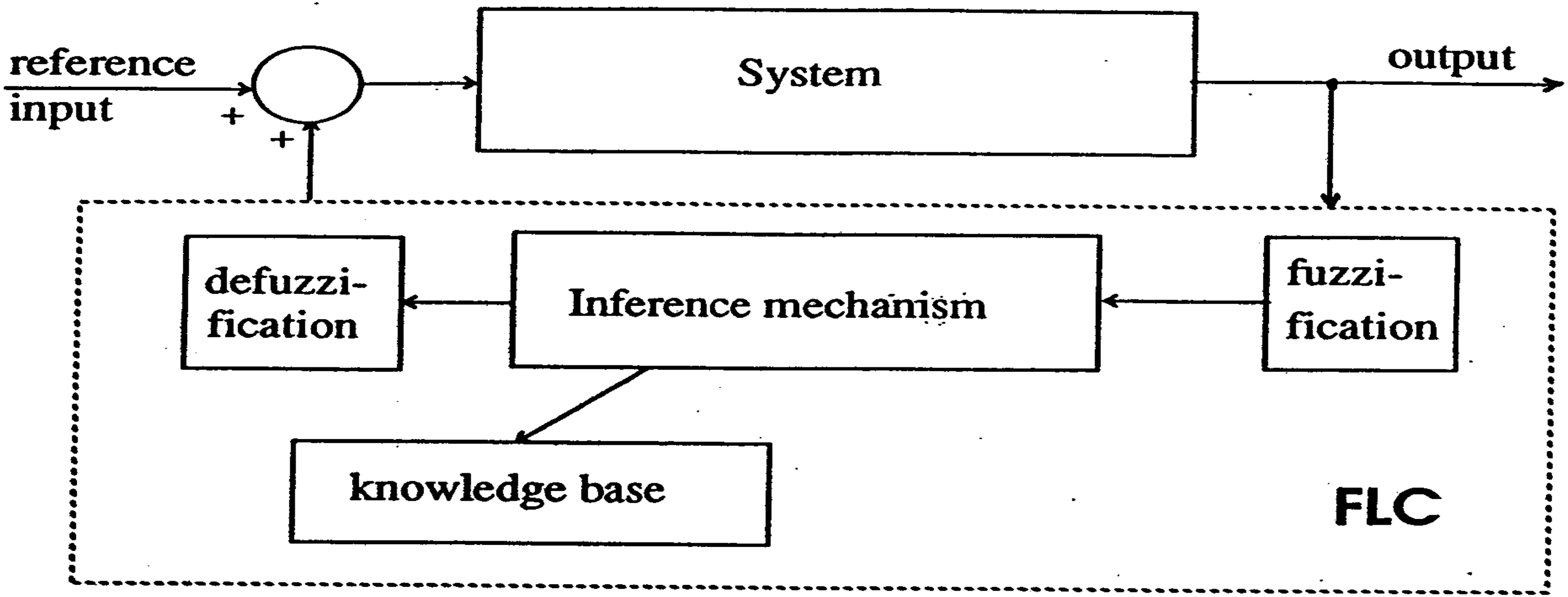


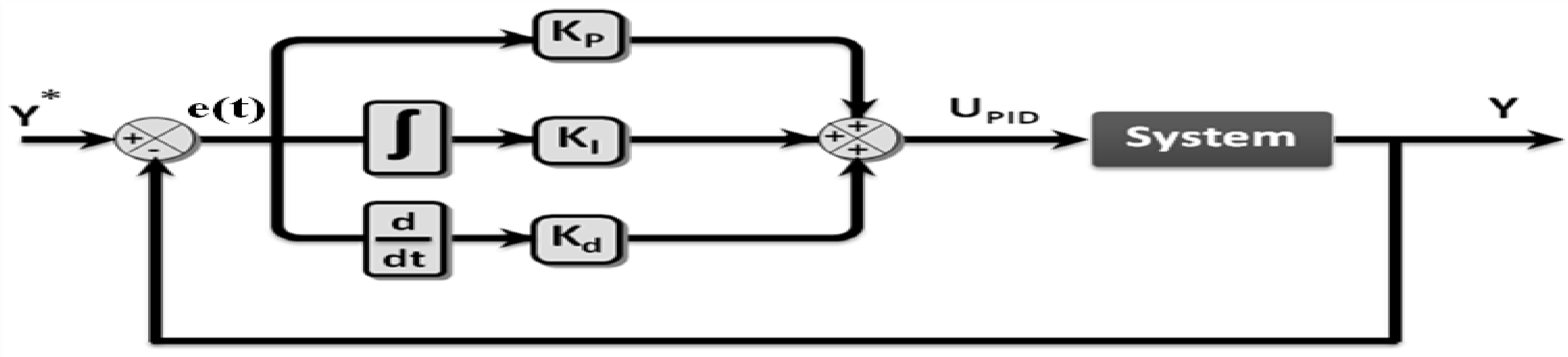
Fig. 3. Nonlinear scaling

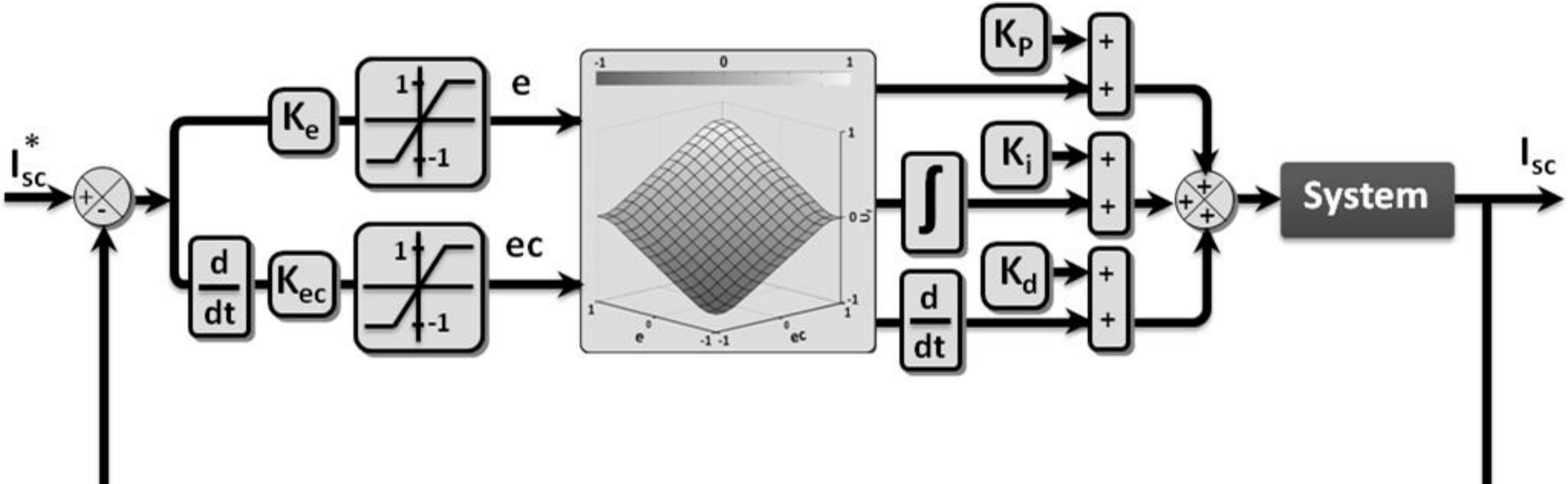

reference
input
+
+
System
output
defuzzi-
fication
Inference mechanism
fuzzi-
fication
knowledge base
FLC

Fuzzy Rules Table

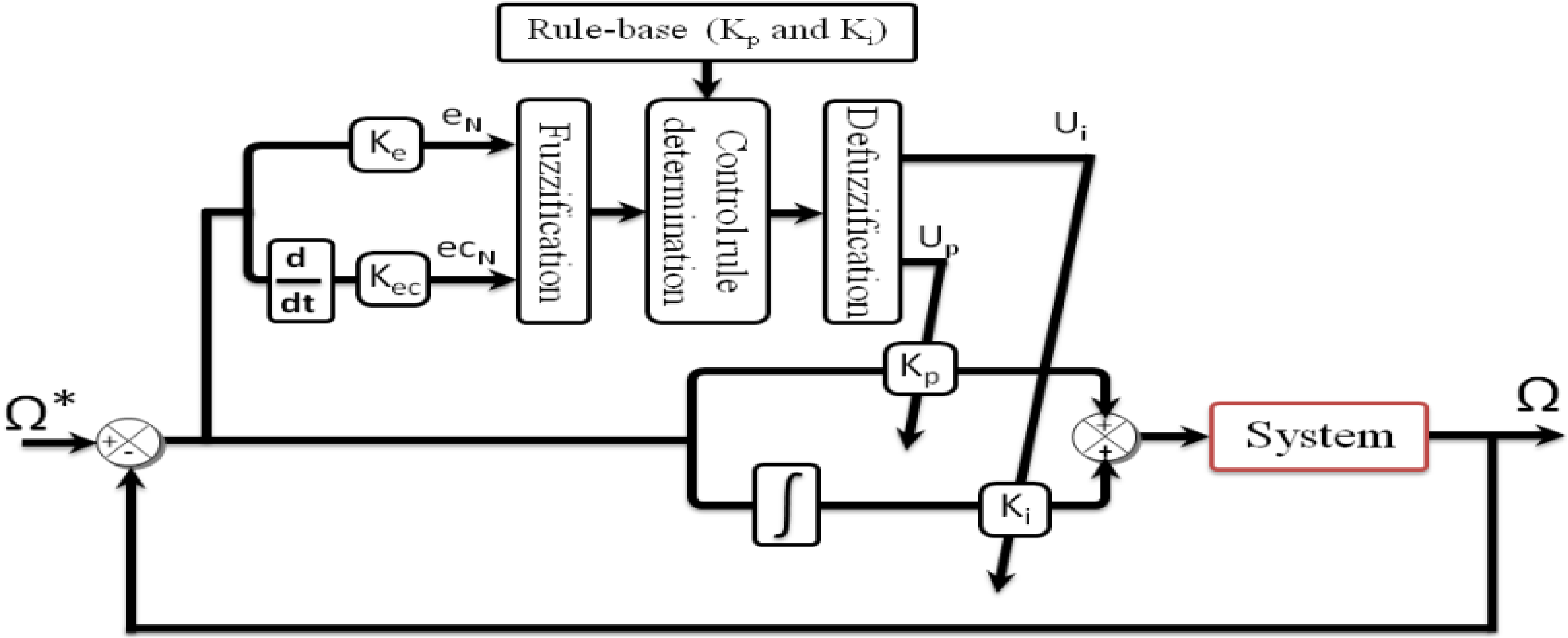
		We				
		NB	NM	Z	PM	PB
	NB	NB	NB	NB	Z	Z
	NM	NM	NB	NS	Z	Z
	Z	NS	NS	Z	PS	PS
	PM	Z	PS	PM	PM	PM
ΔWe	PB	Z	PM	PB	PB	PB

Conventional and Fuzzy PID Algorithm

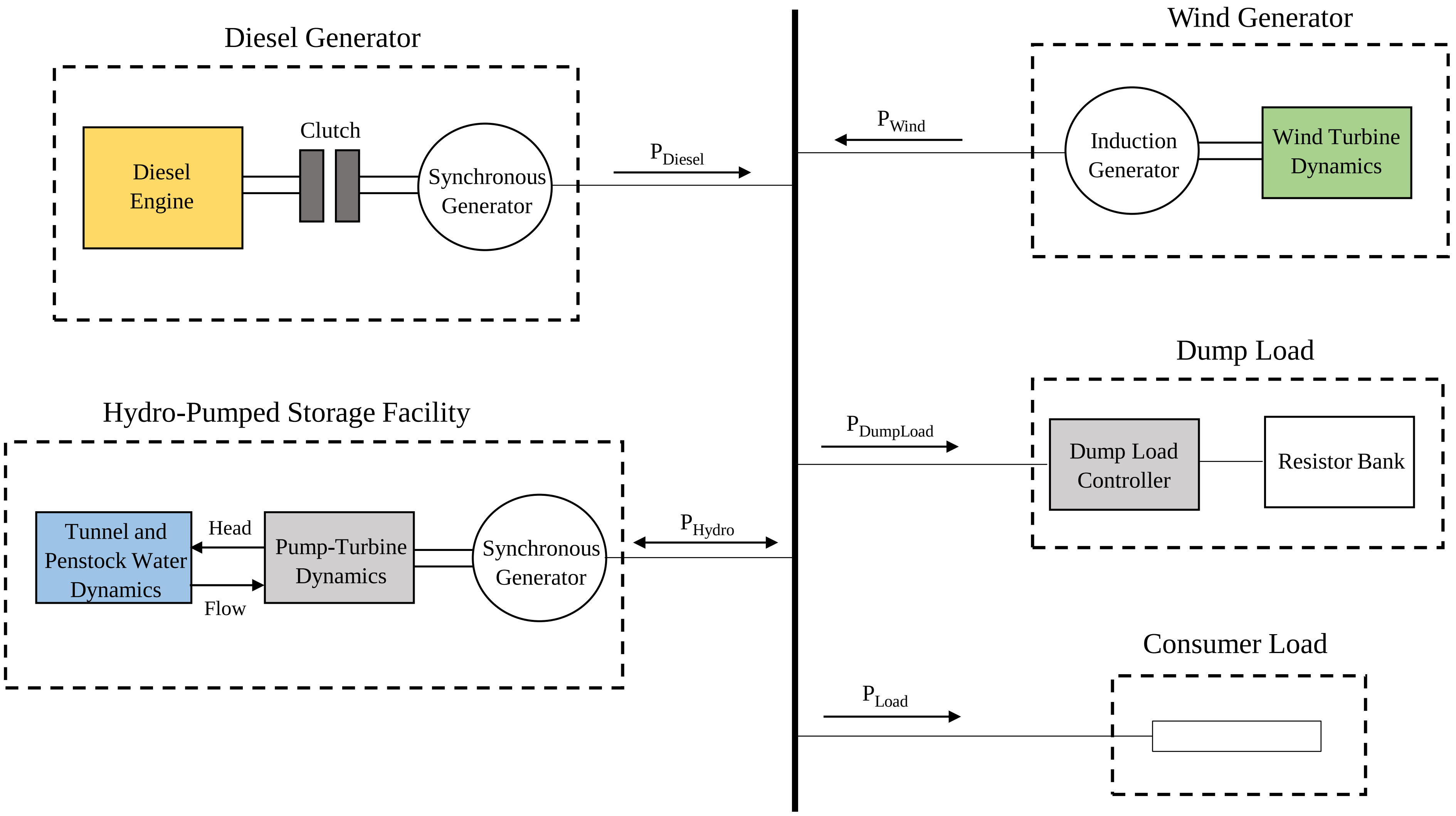




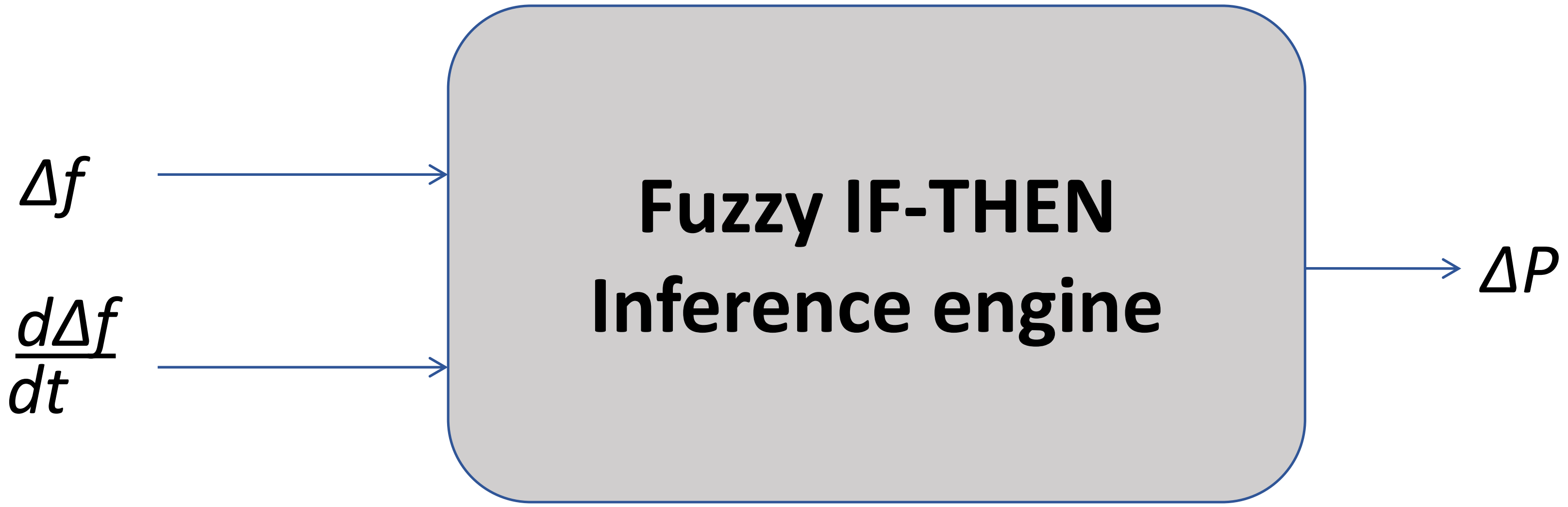
Fuzzy Logic Self-tuning PI Algorithm



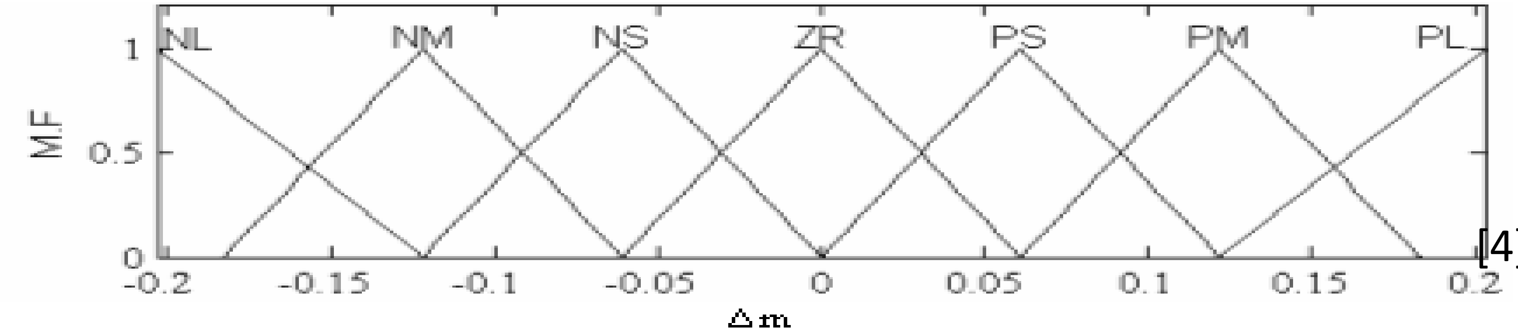
Hybrid Micro-Grid Configuration



Dump Load Frequency Control

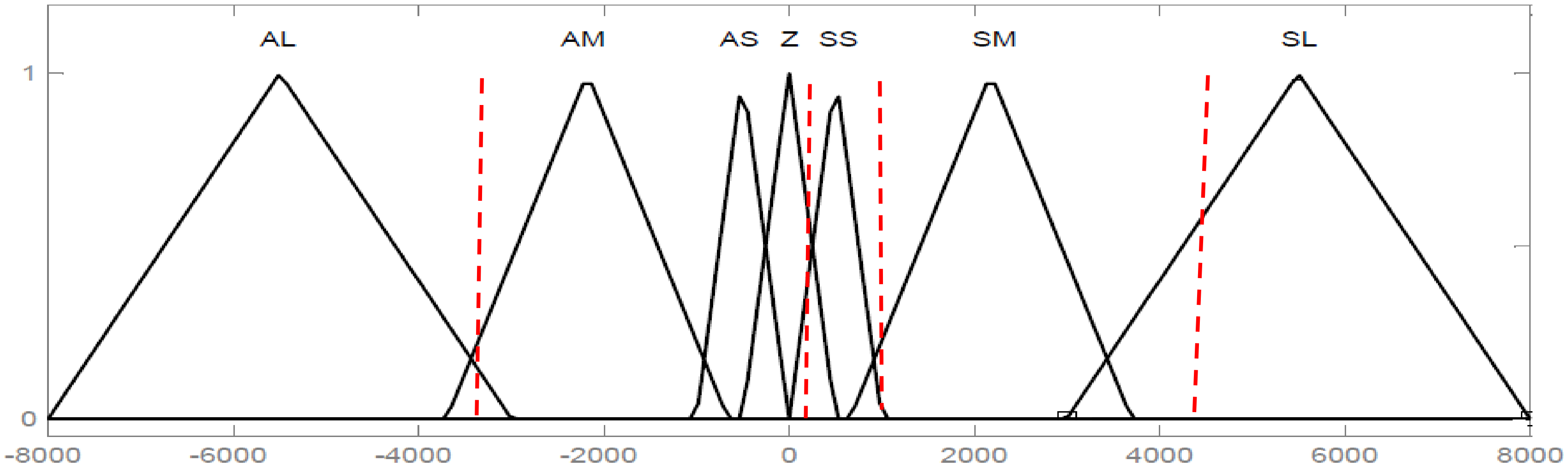


DL frequency control



[4]

Previous fuzzy frequency control

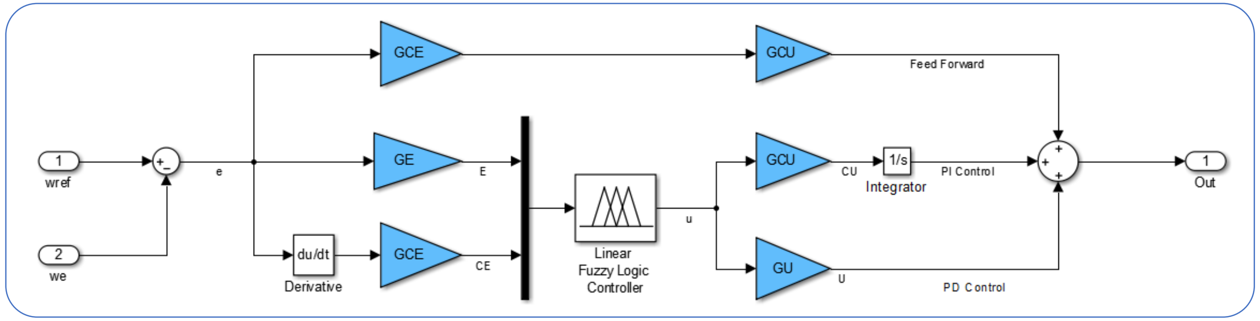


Proposed fuzzy controller

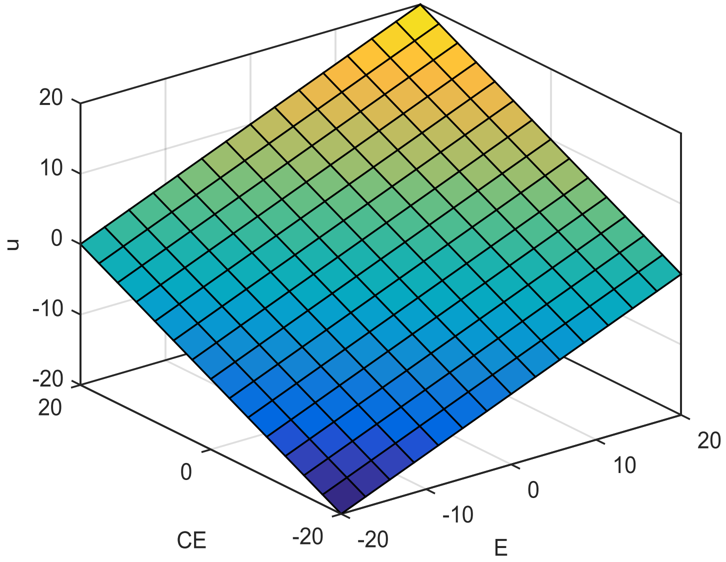
1. *Large* membership functions reduce the regulation time
2. *Small* membership functions reduce oscillations around settling point

HPS Turbine Mode Controller

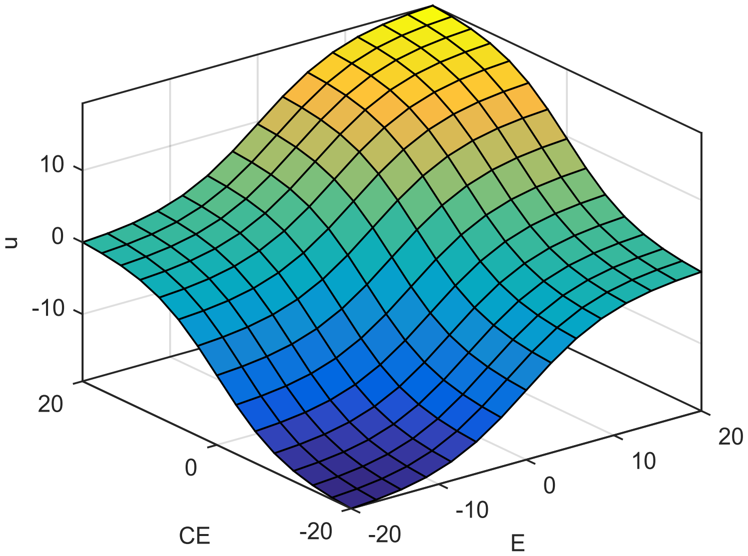
Simulink Fuzzy PID Controller Model



Linear Fuzzy PID Controller

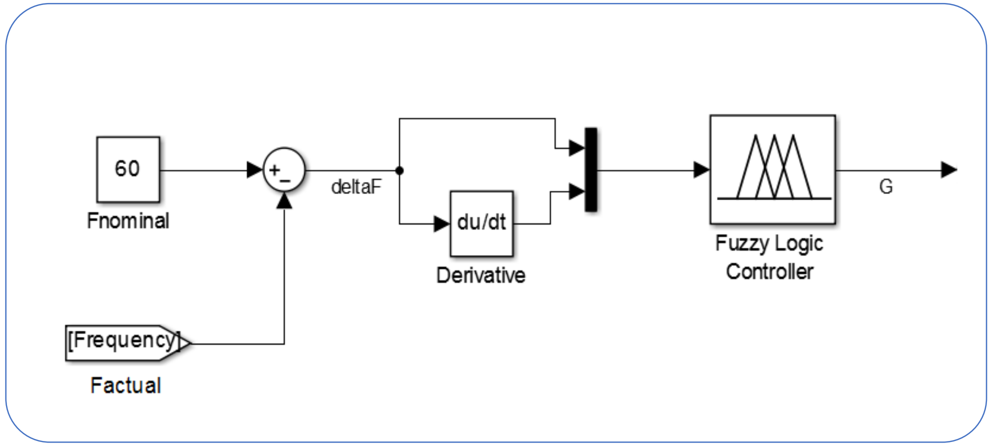


Non-Linear Fuzzy PID Controller

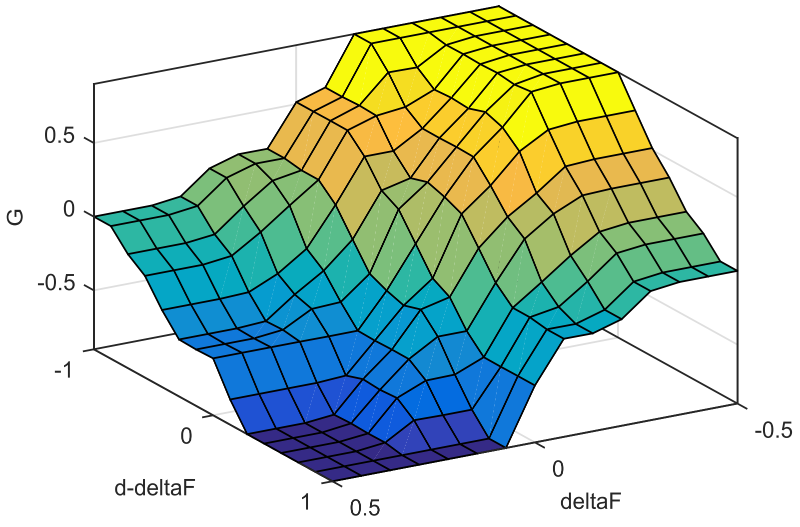


HPS Pumping Mode Controller

Simulink Fuzzy Logic Controller Schematic



Fuzzy Logic Controller
Control Surface



SCHULICH School of Engineering

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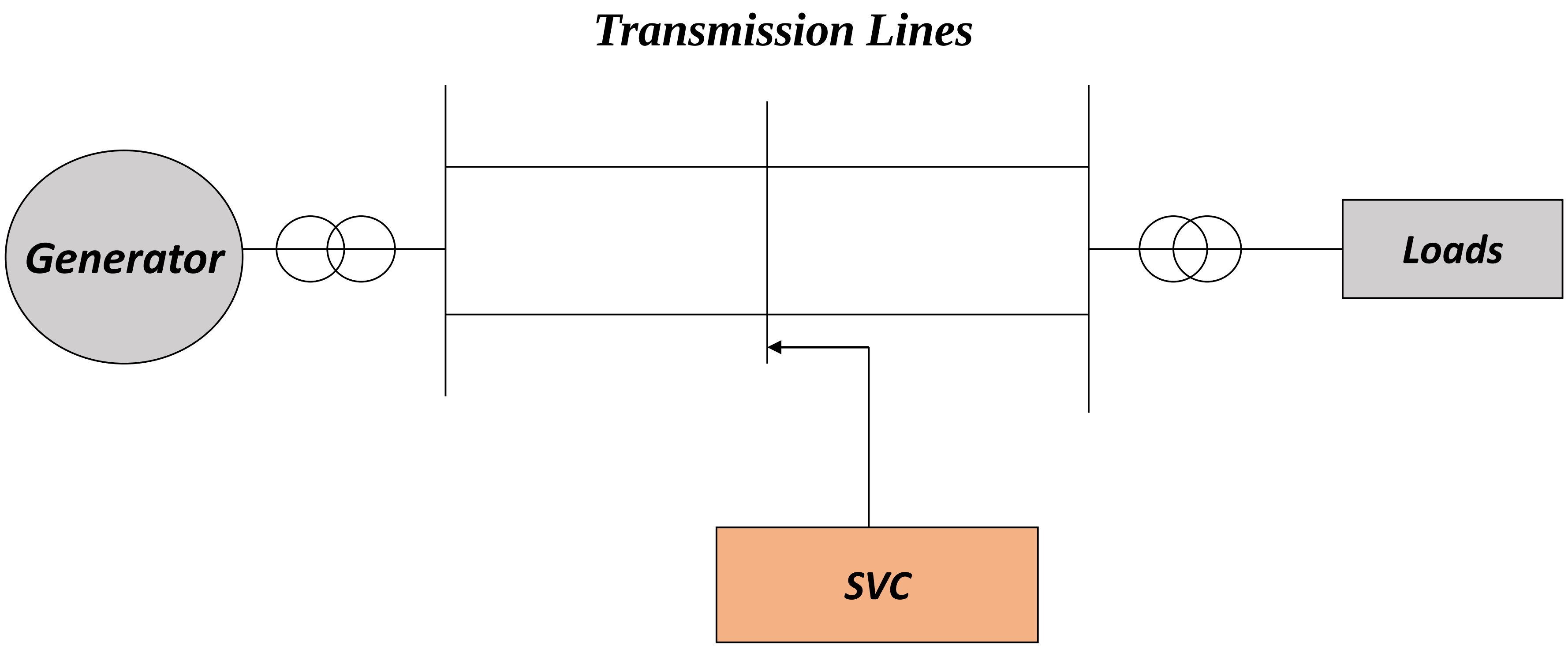
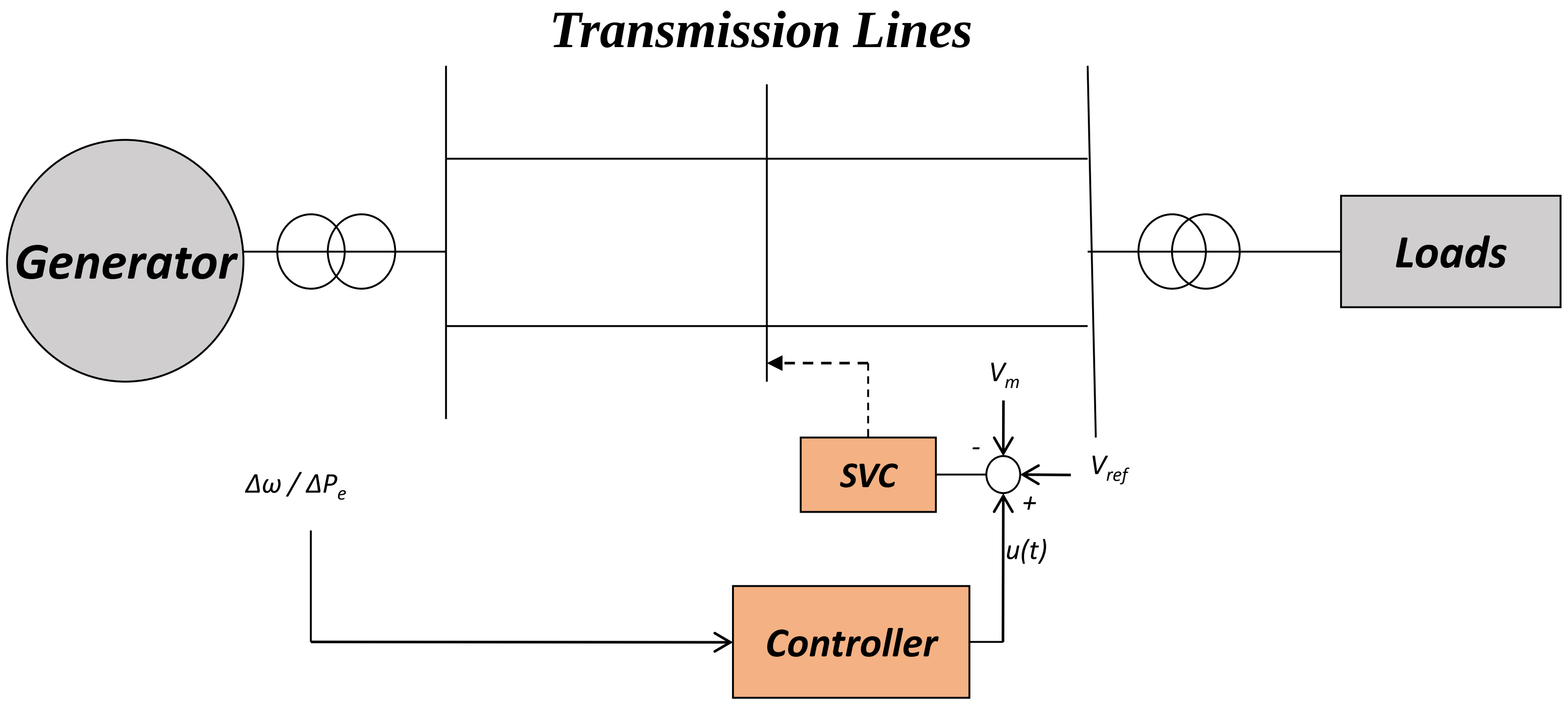
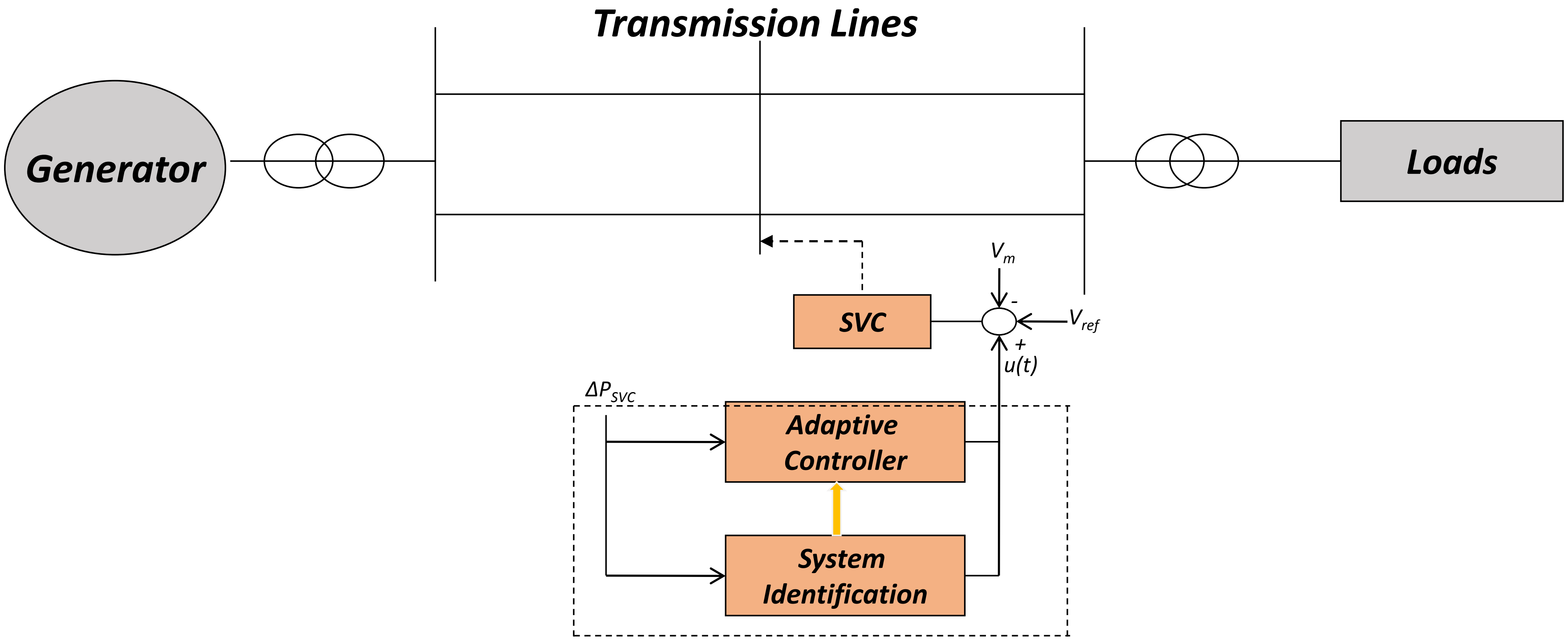


Power system diagram including SVC Device



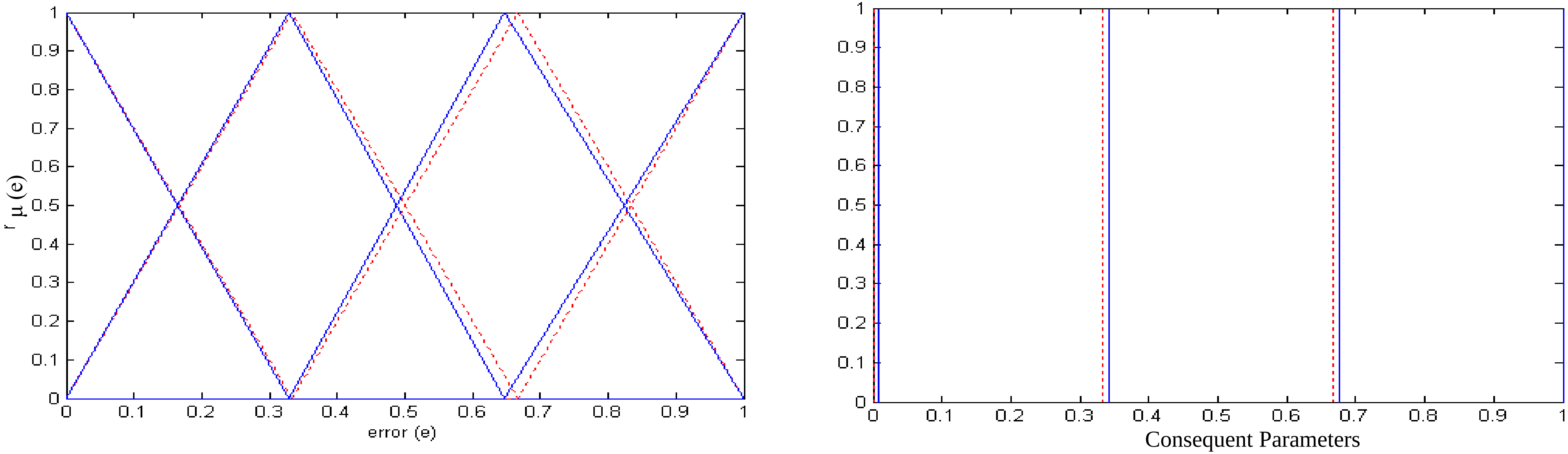
Classical control approach for a FACTS device

Proposed Solution



Proposed adaptive control system structure for SVC device In a SMIB system

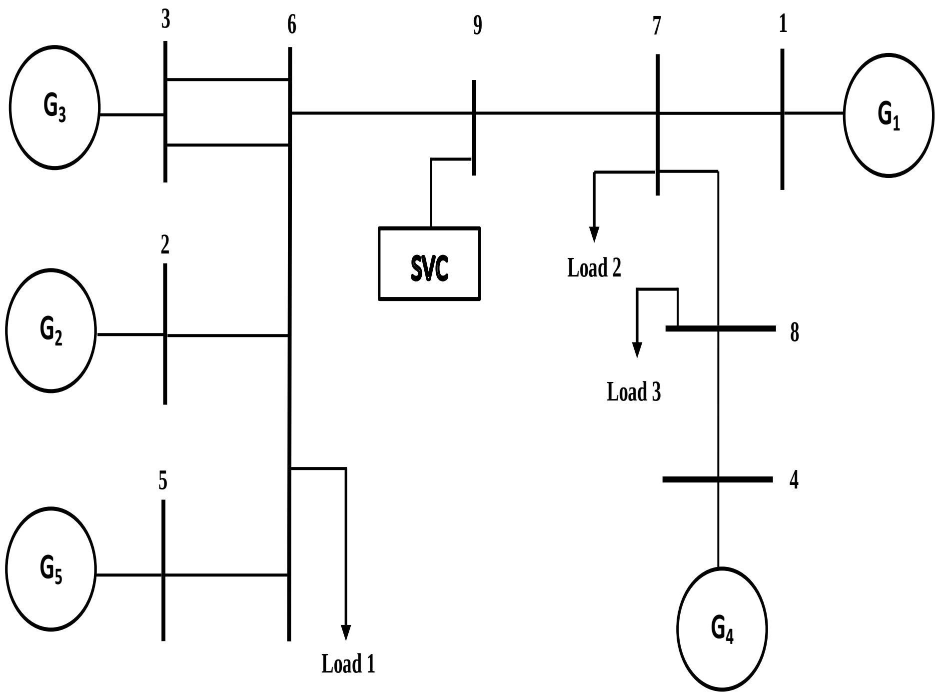
Single Machine Infinite Bus System Simulati Results



Example of membership function before and after adaptation

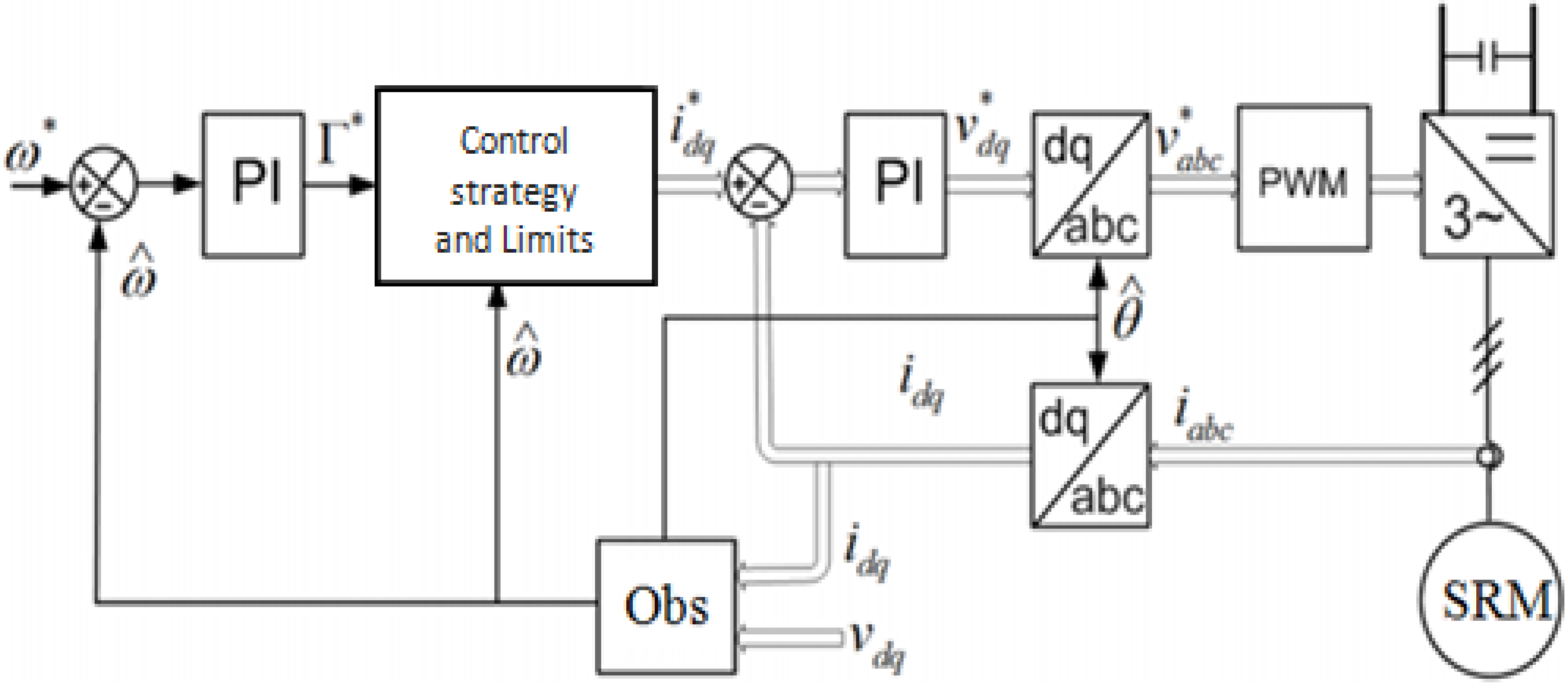
………. Before adaptation ——— After adaptation

Multi-machine System Simulation Results

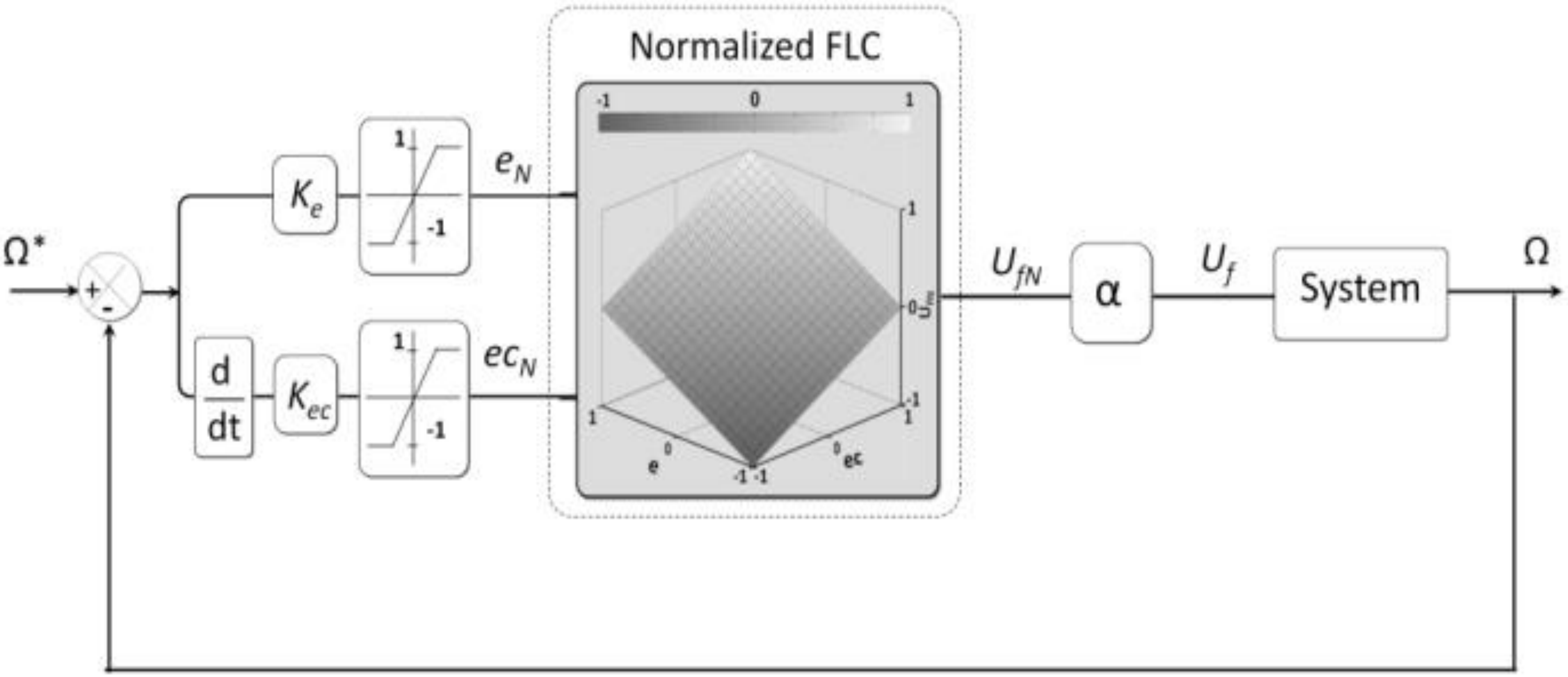


Schematic model of a multi-machine power system with an SVC device installed at the middle of the tie-line

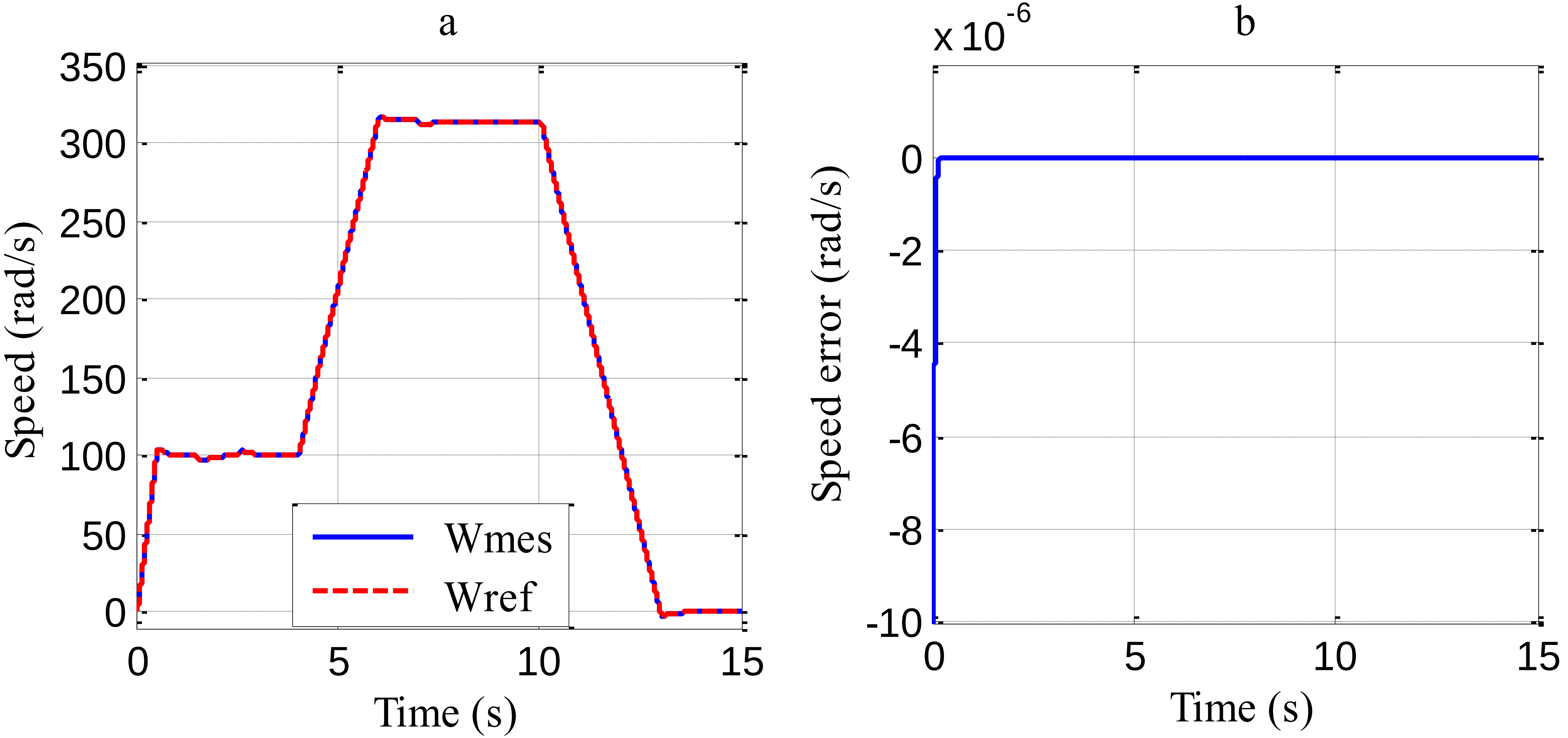
Sensorless Control of a Switched Reluctance Machine



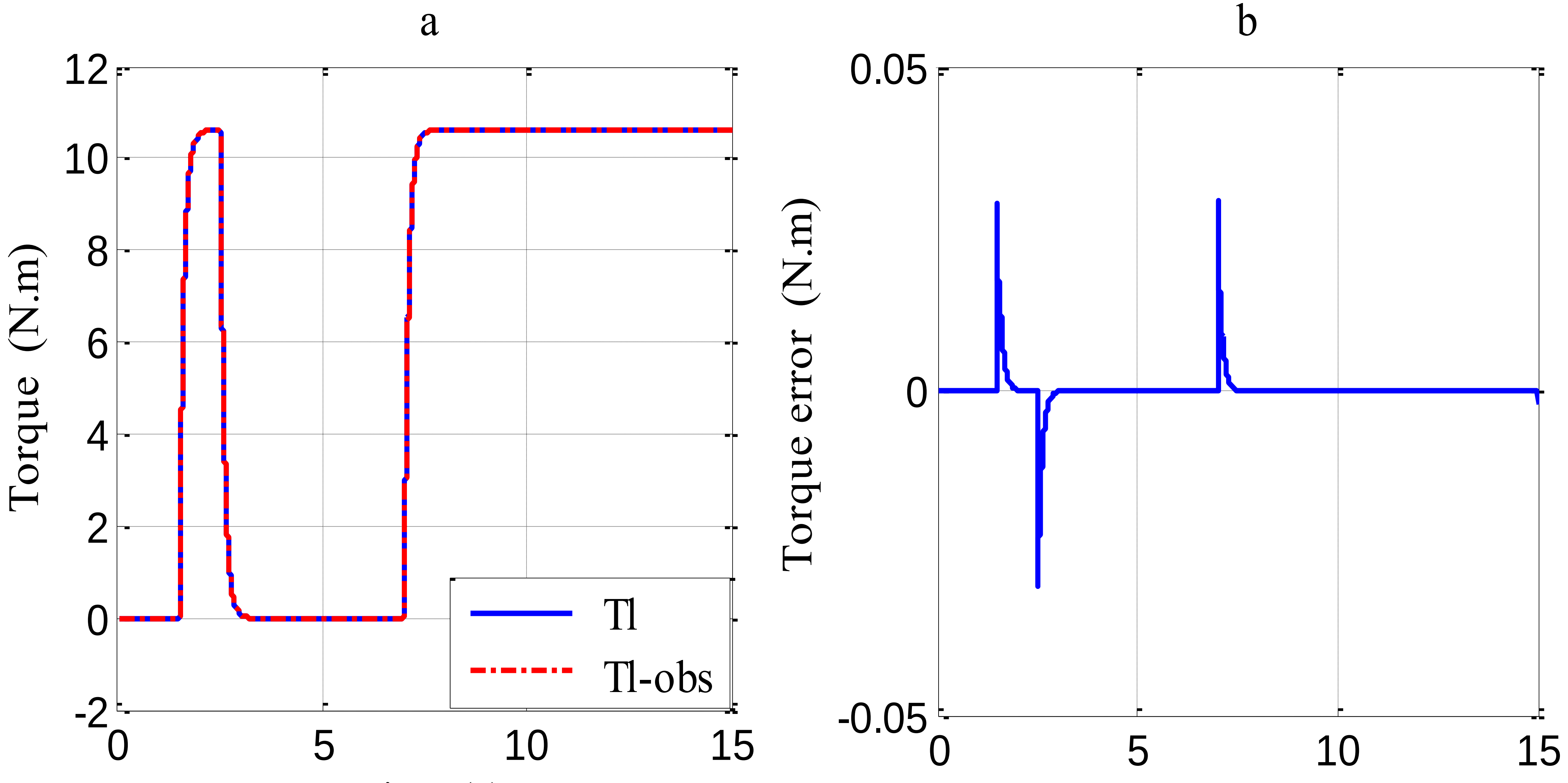
Fuzzy Logic Controller for SRM



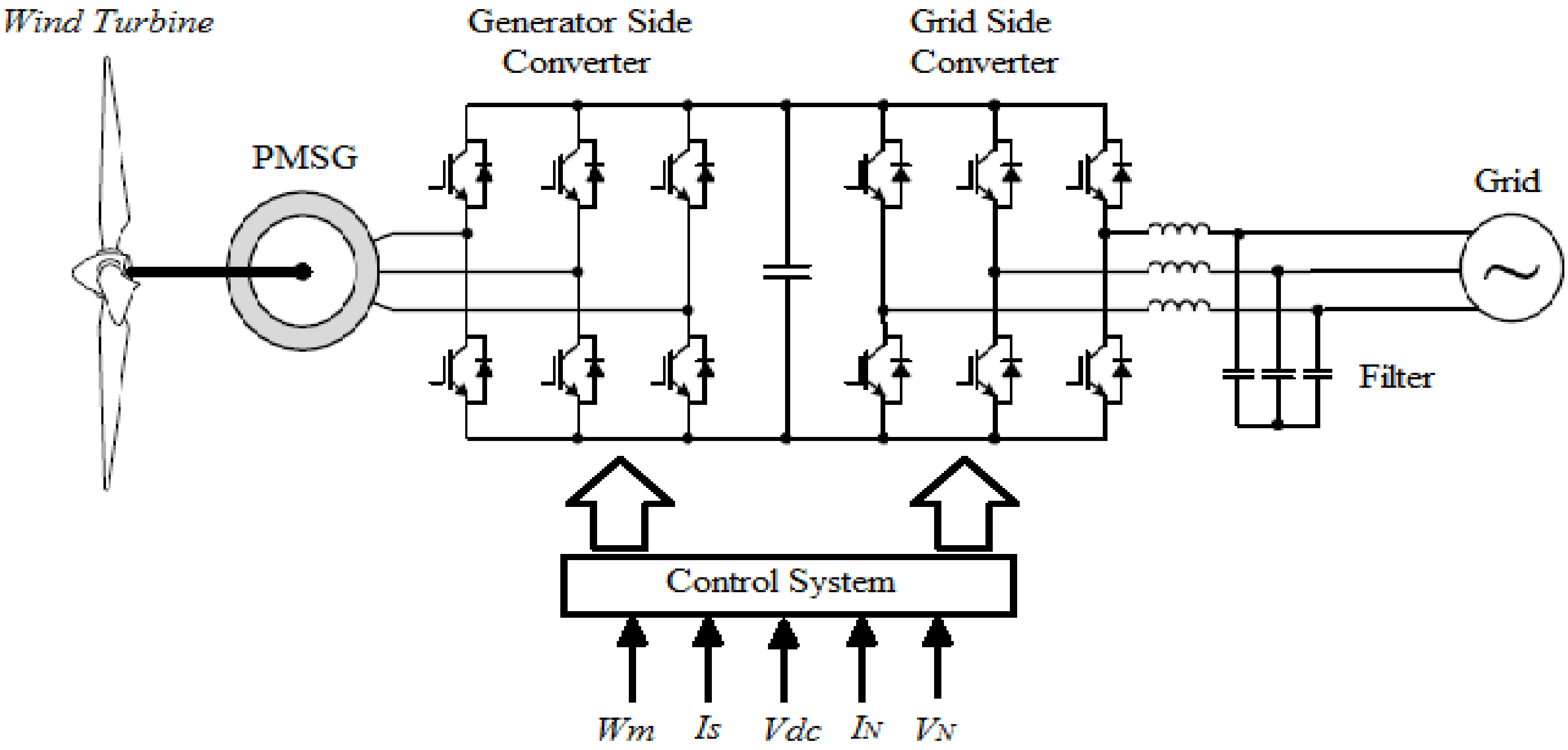
Speed Tracking SRM



Estimated and Real Load Torque SRM



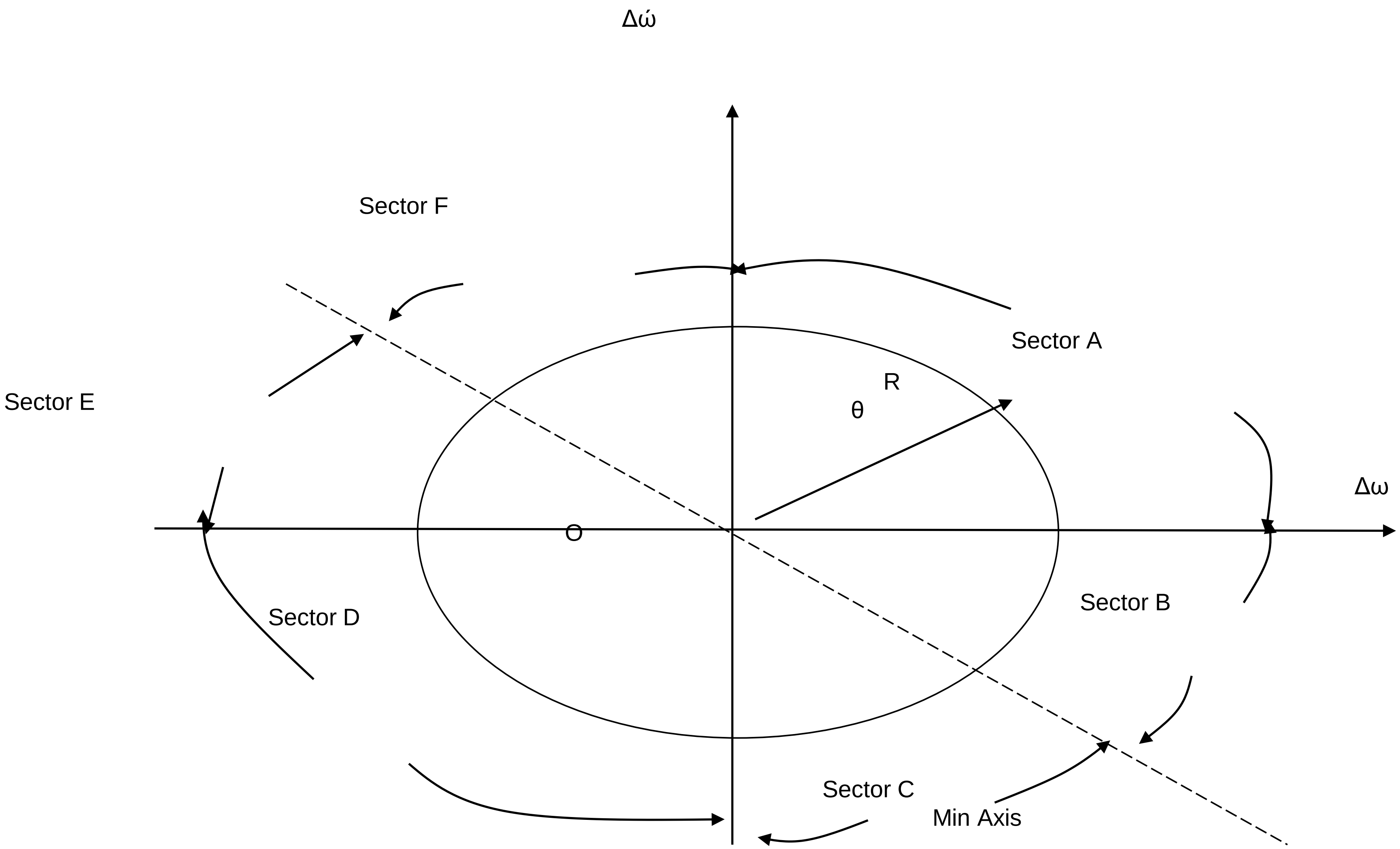
Permanent Magnet Synchronous Generator WECS



Field Oriented Control of Stator Side Converter of PMSG

- D-Q components of the stator reference voltages, that ultimately control the rectifier firing angle, are generated by two PI controllers with d-q components of the stator currents as inputs.
- Conventional PI controllers are replaced by trained ANFIS with d-q axes stator currents error and integral of error as inputs.
- Applied to a 1.5 MW wind turbine system with PMSG

Six sector phase plane



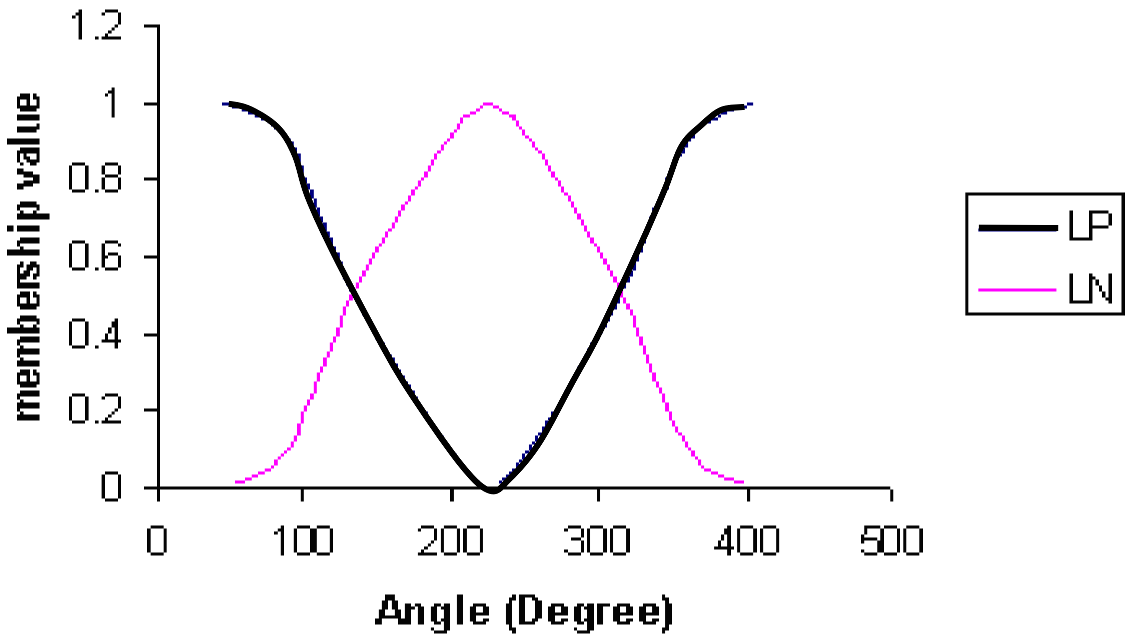
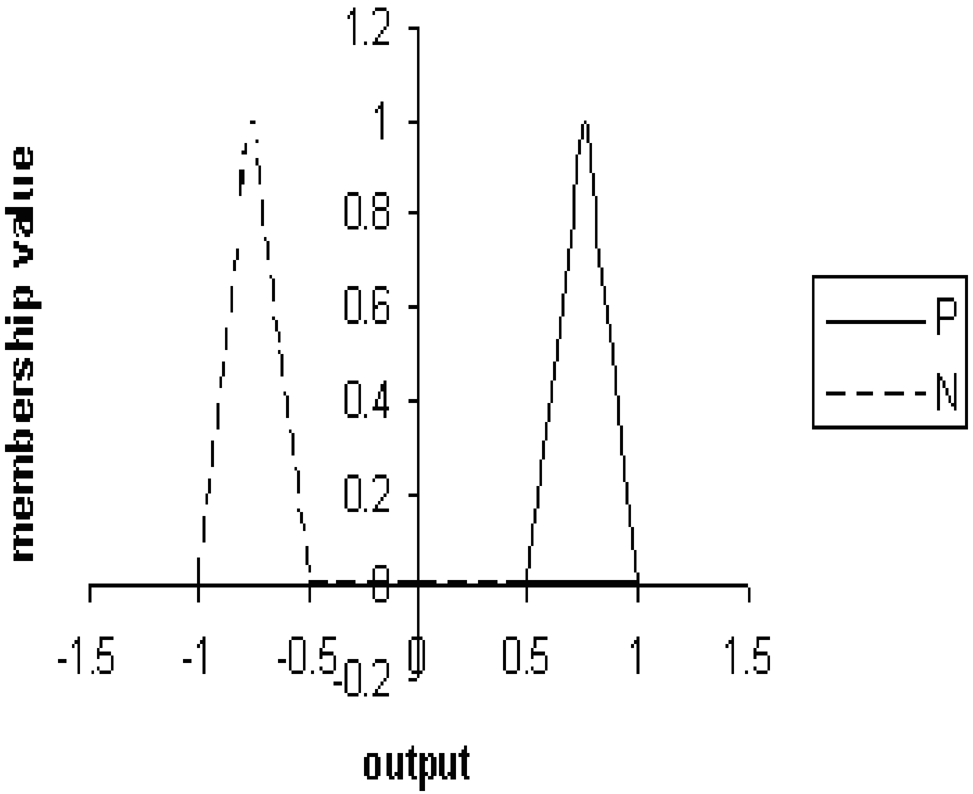
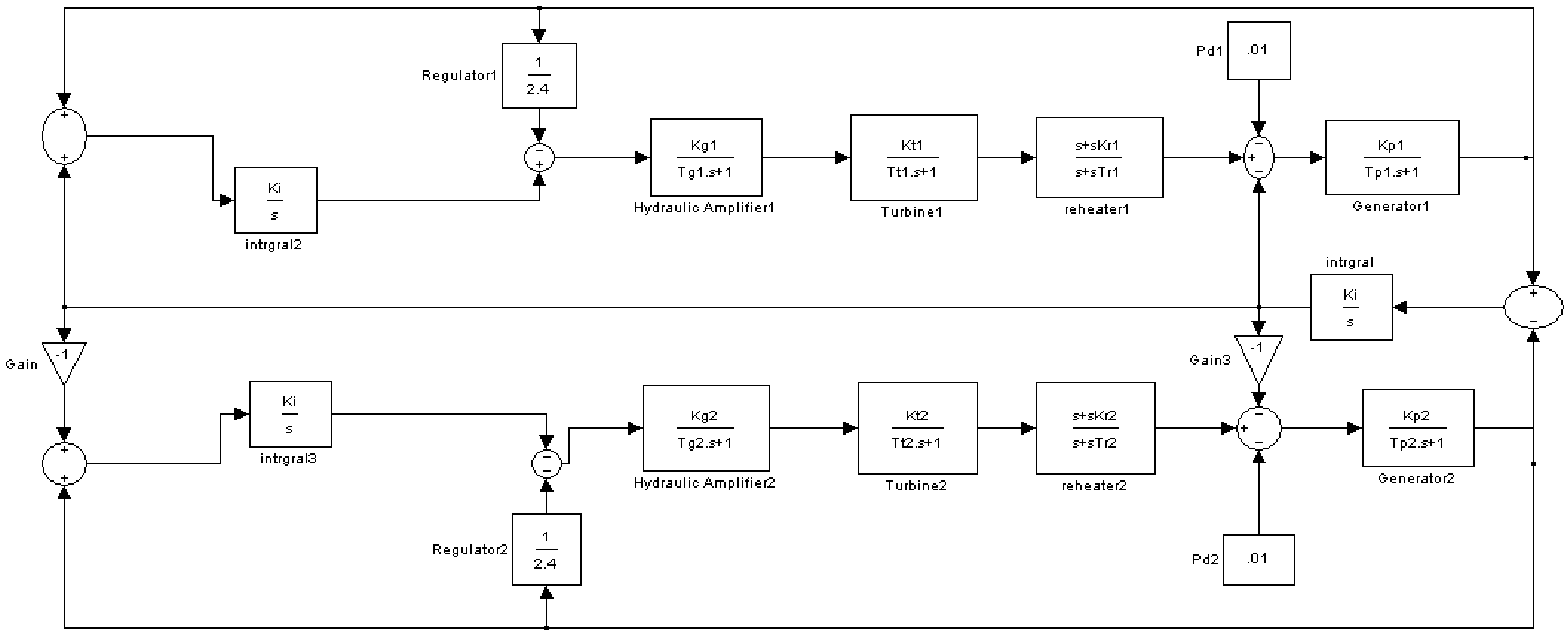


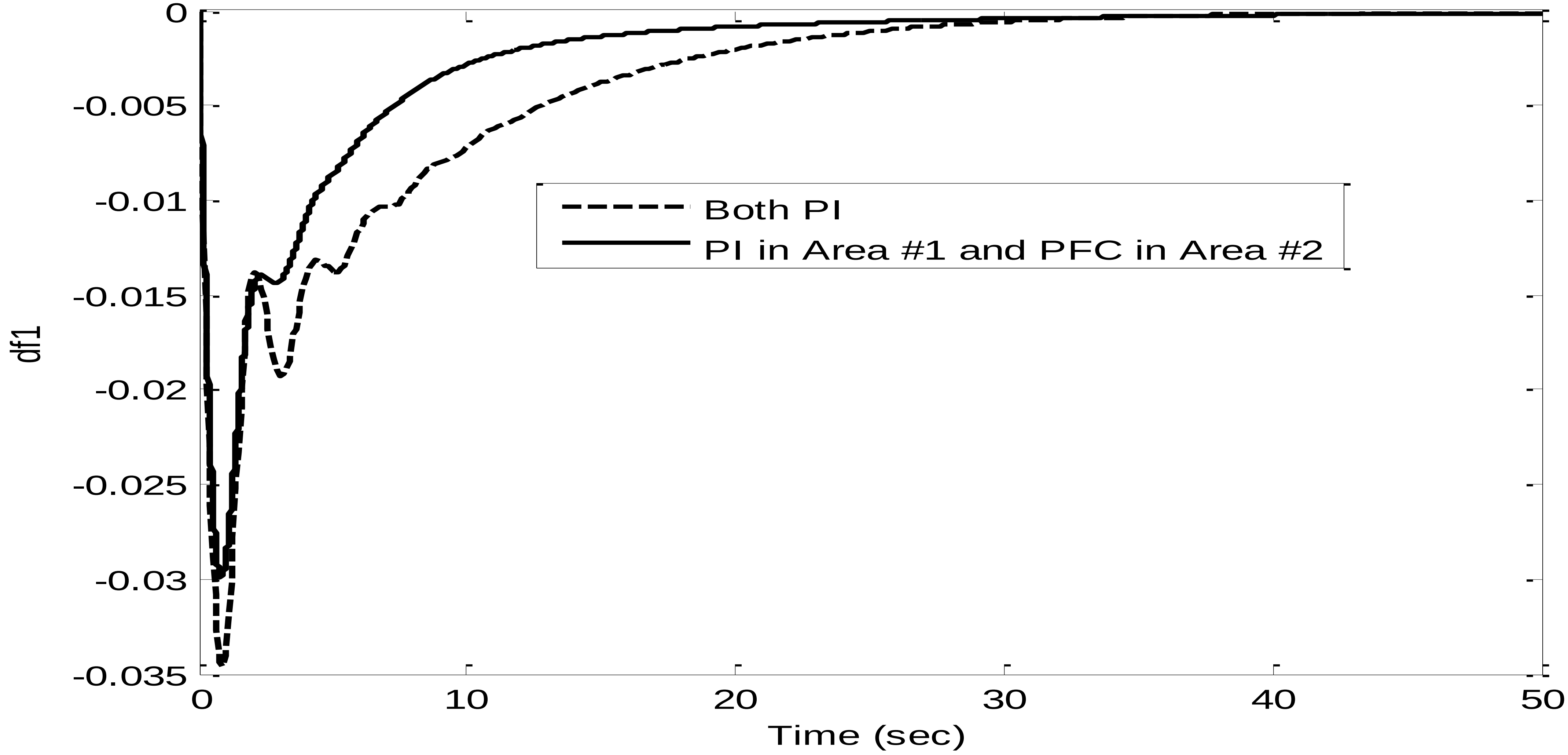
Fig. 6 Fuzzy sets for input variable



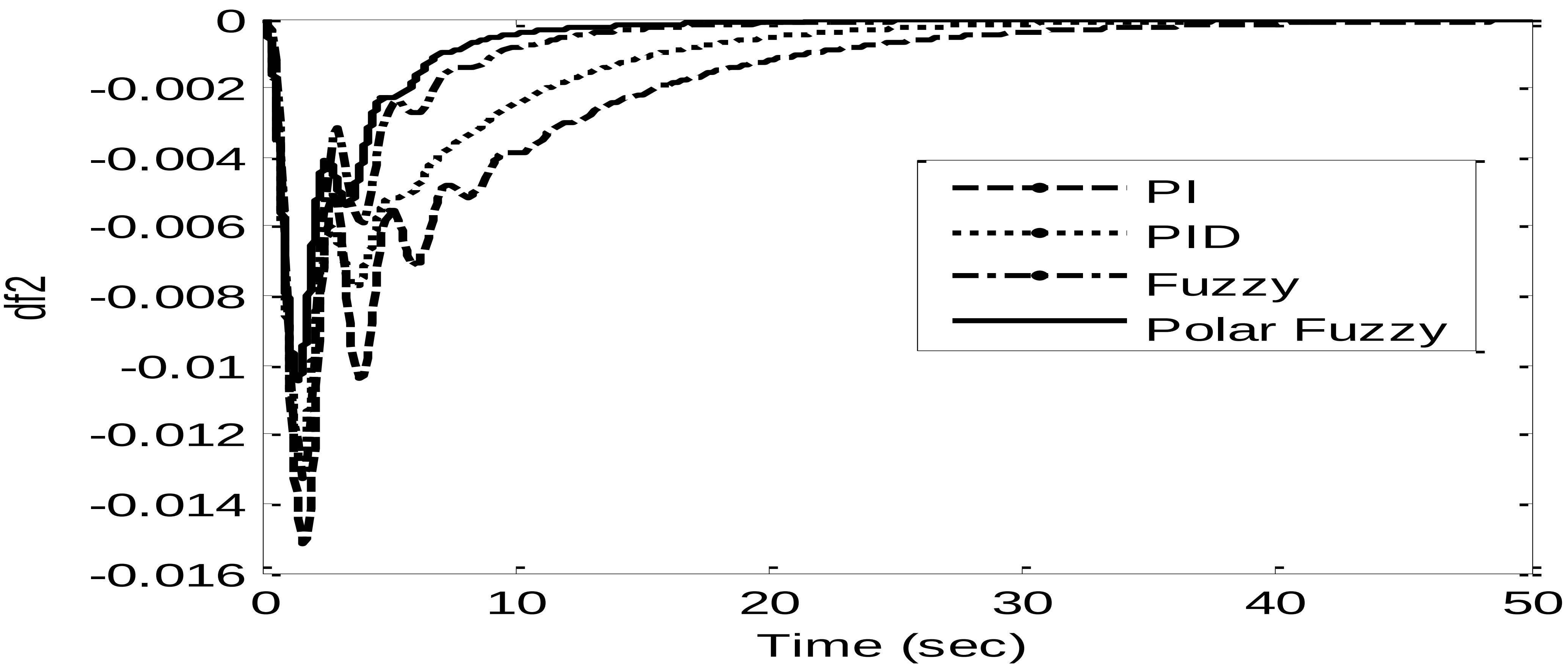
Two Area Power System for LFC



Frequency variation of area- 1 in a Two Area Thermal System without Reheat unit when disturbance in both areas



Frequency variation of area- 2 in a Two Area Thermal System without Reheat unit when disturbance in area - 1

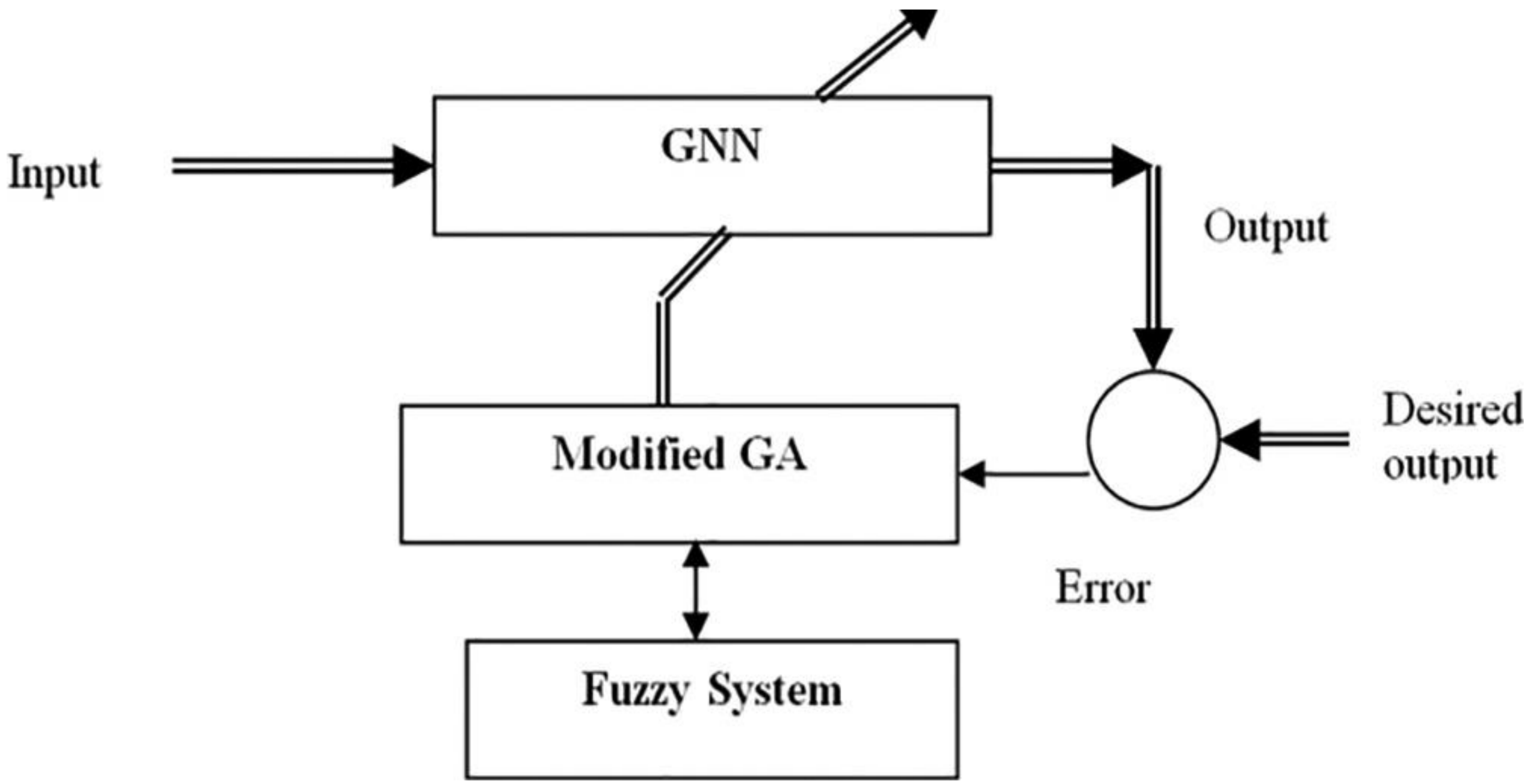


Short Term Load Forecast

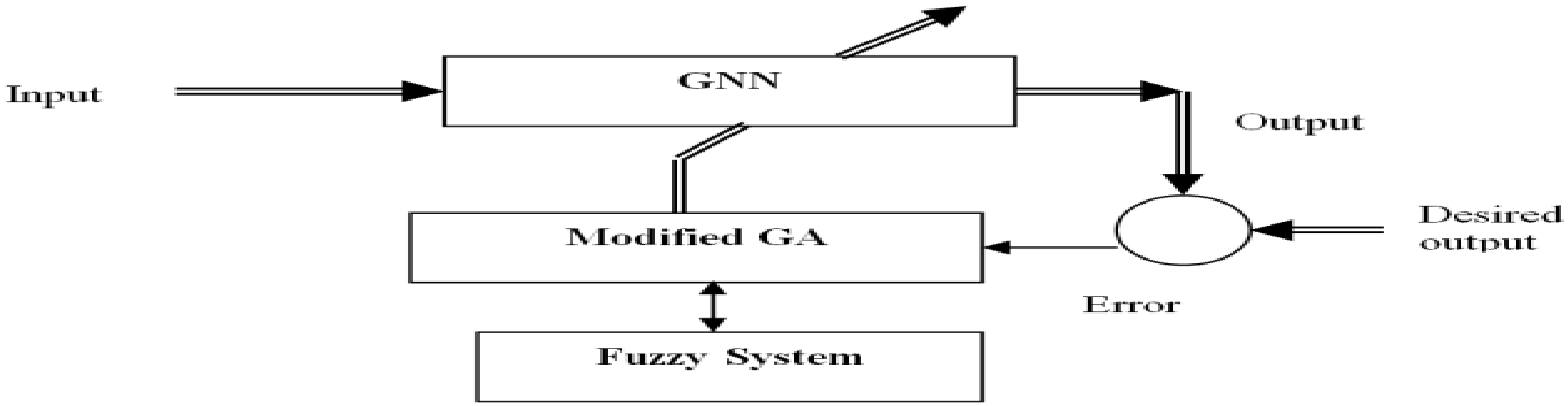
- Statistical methods
- AI based methods employing both neural networks and fuzzy logic

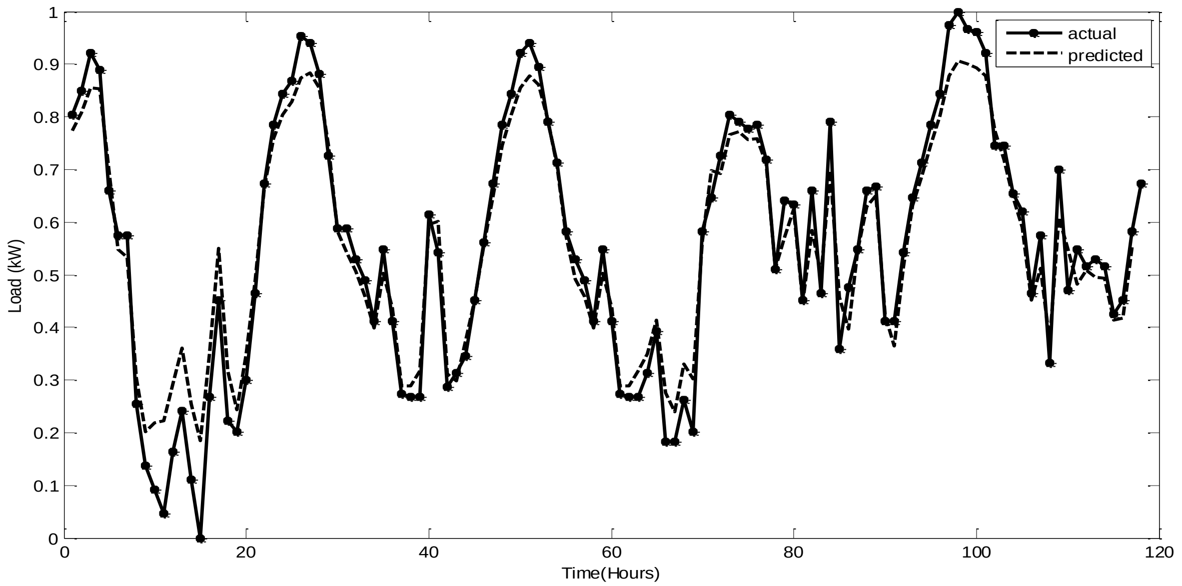
- Neural networks need to be trained
- Using heuristic optimization techniques, e.g. GA, that employ random search and fuzzy rules to guide search, performance can be improved.
- A generalized neural network (GNN) with four wavelet components of the historic load data as input and fuzzy logic guided random search GA as a learning tool for the GNN is used for short term load forecast.
- RMS error with:

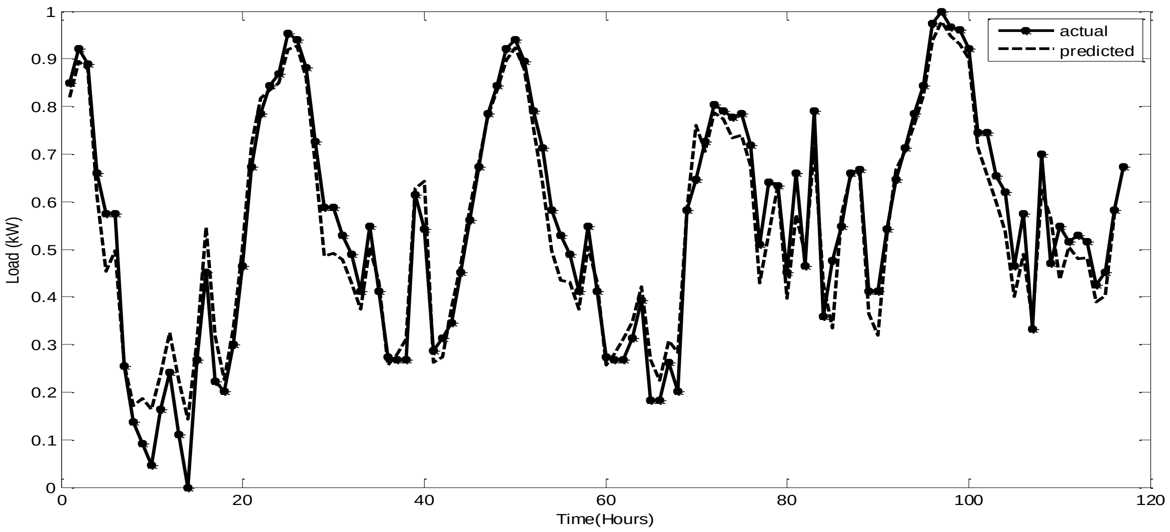
back propagation training – 0.0610 GAF training – 0.0486


GNN
Input
Output
Modified GA
Desired output
Error
Fuzzy System

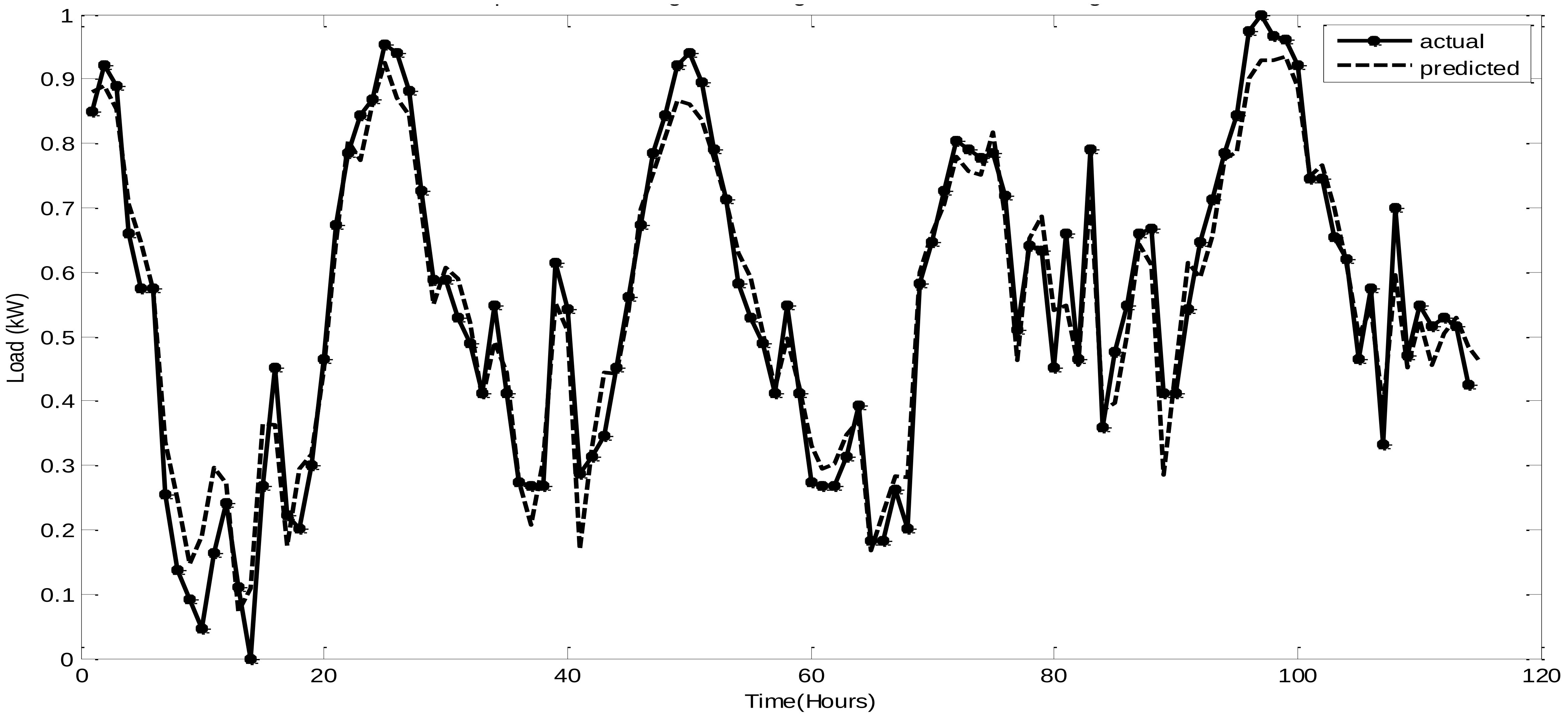
Short Term Load Forecast with FL and GNN



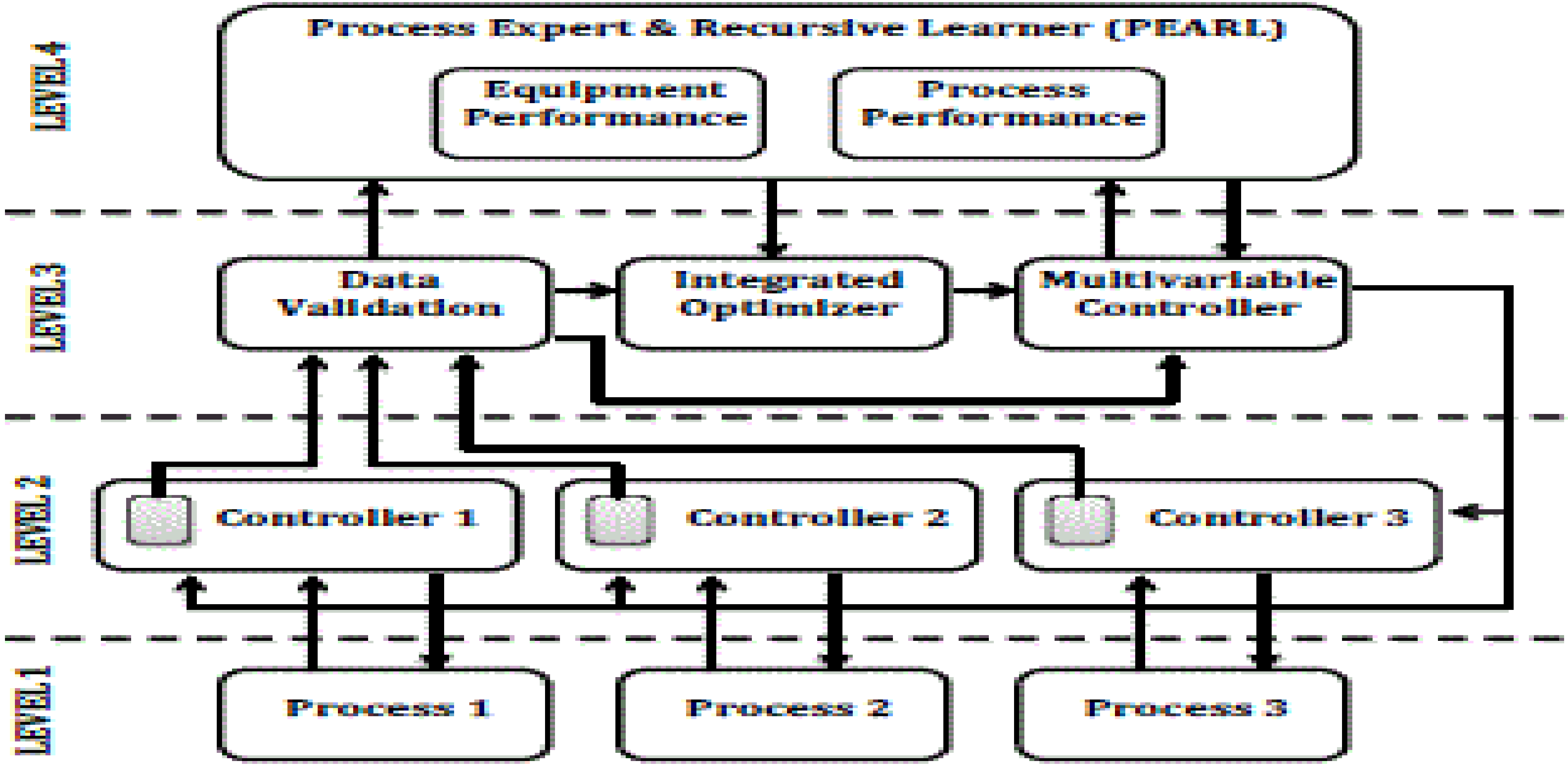




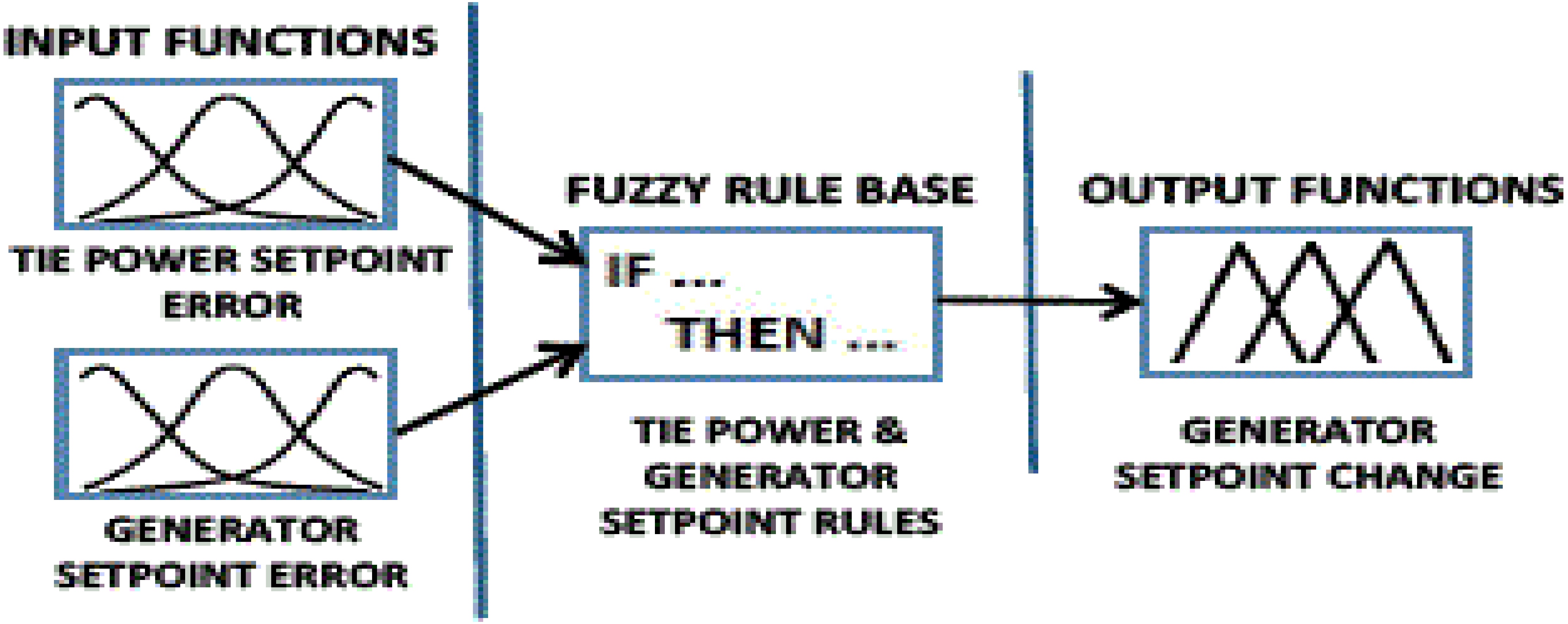
Self-Tuning Load Forecast using GNN-W-GAF

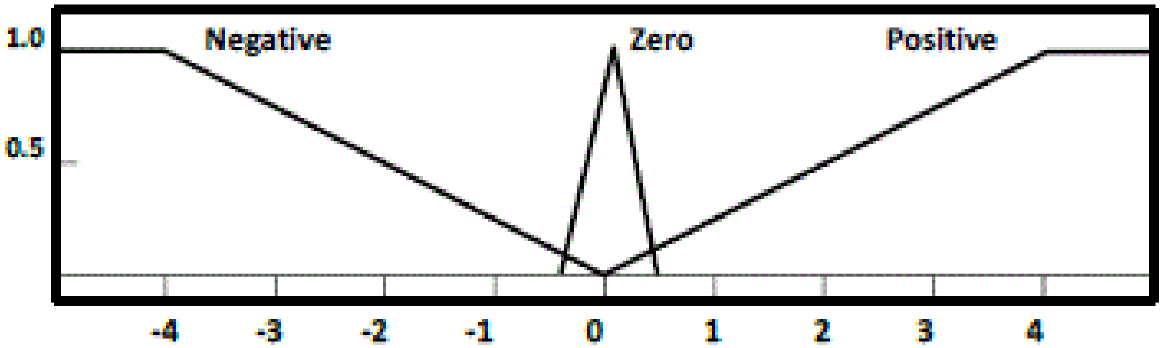


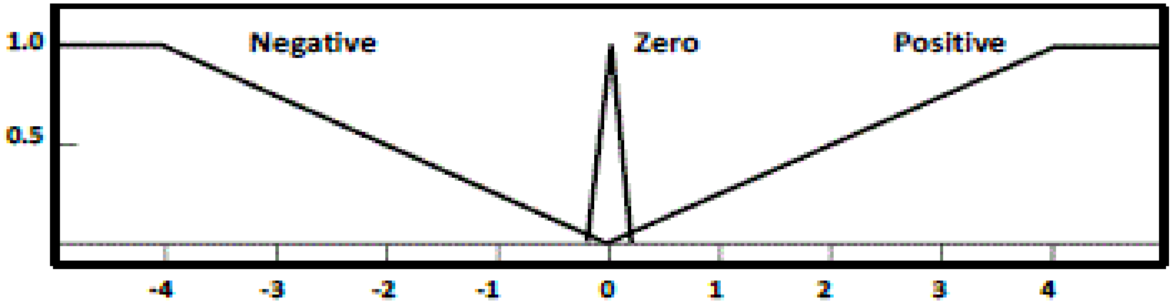
Supervisory Control of a Cogeneration Plant

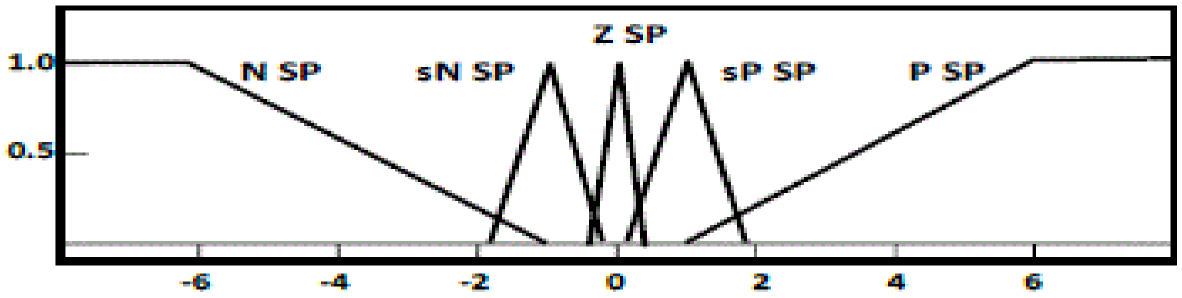


Generator Fuzzy Set-Point Control

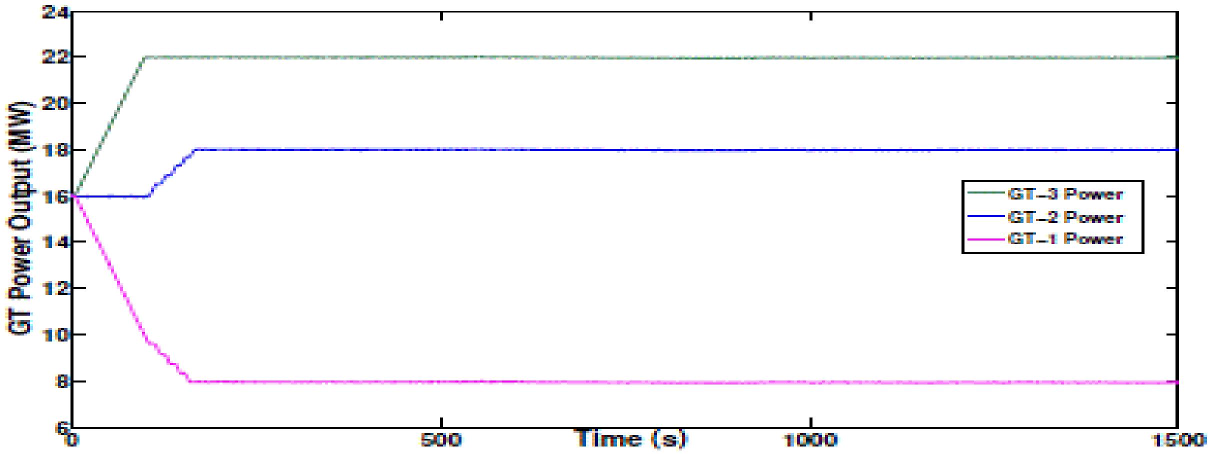




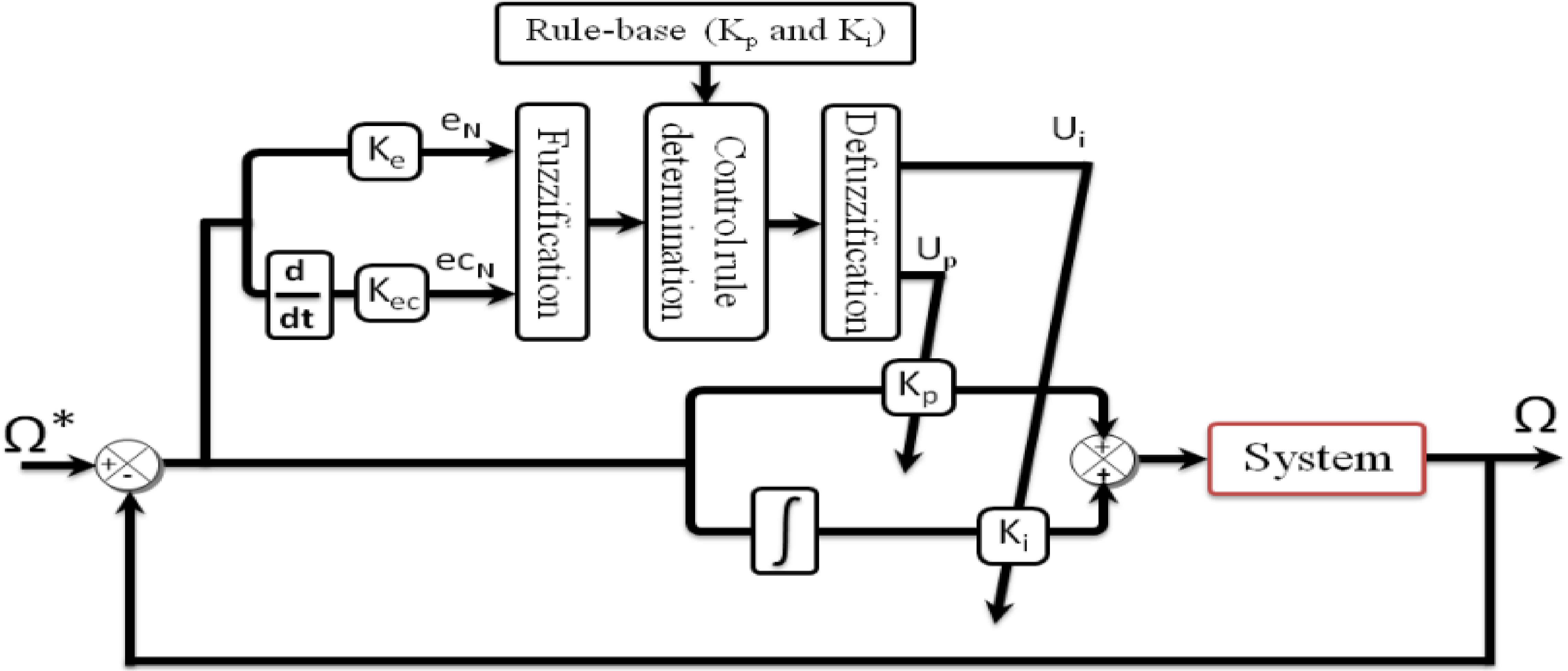




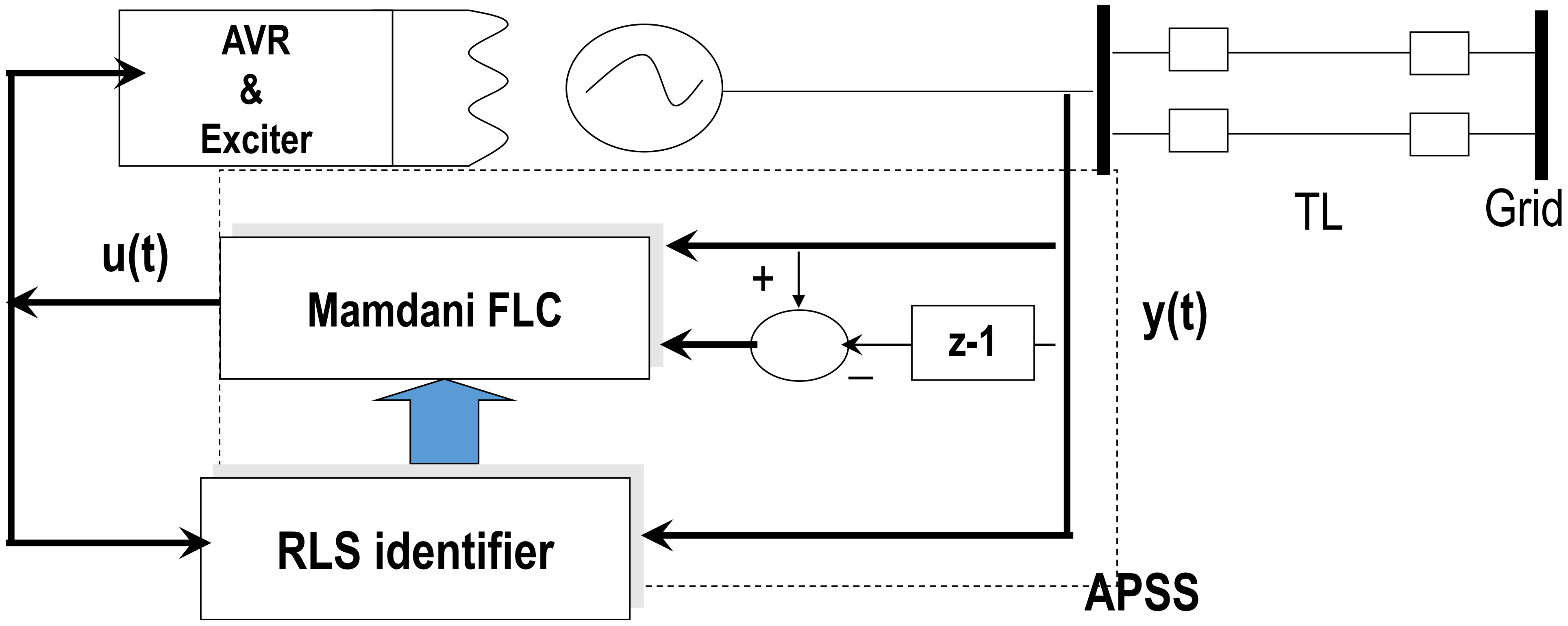
Tie Power Error \ GT Setpoint Error	Positive	Zero	Negative
Positive	N SP	Z SP	Z SP
Zero	sN SP	Z SP	sP SP
Negative	Z SP	Z SP	P SP



Fuzzy Logic Self-Tuning PI Controller

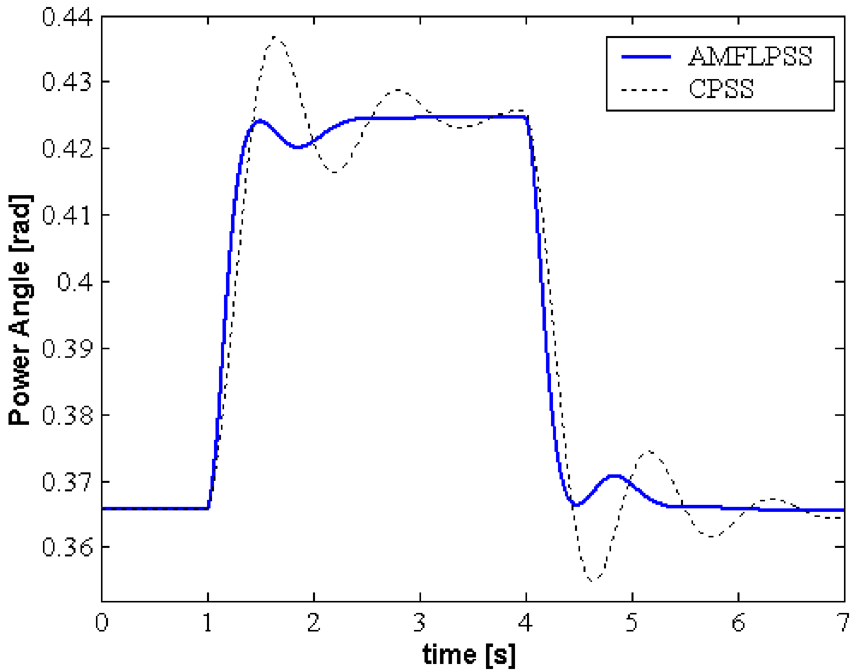


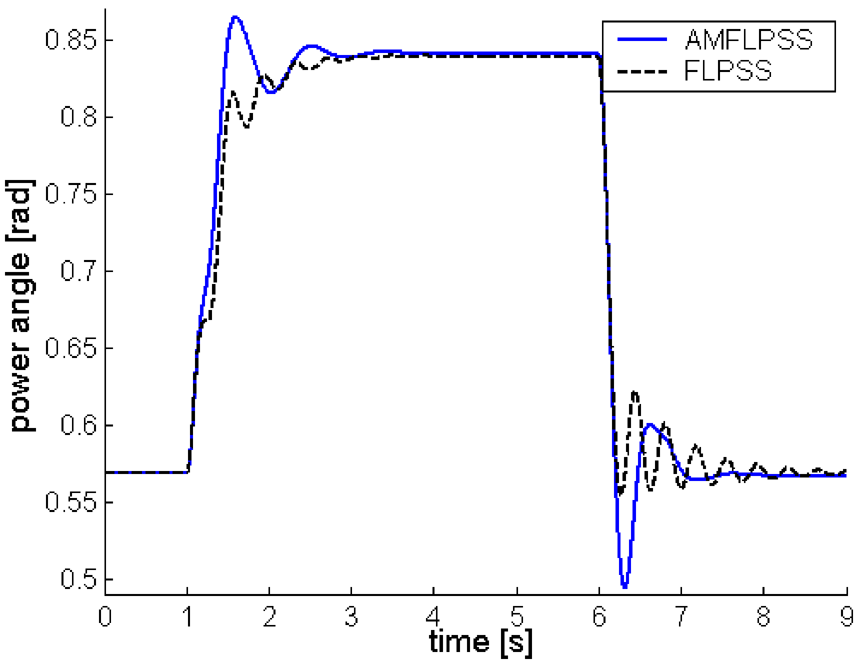
Fuzzy Adaptive Control PSS



RLS identifier and a self-learning Mamdani fuzzy logic controller.

Results





0.1 *p.u.* step increase in torque and return to initial condition

(power 0.30 *p.u.*, 0.9 pf lead)

3 phase to ground fault at the middle of one transmission line and successful re-closure

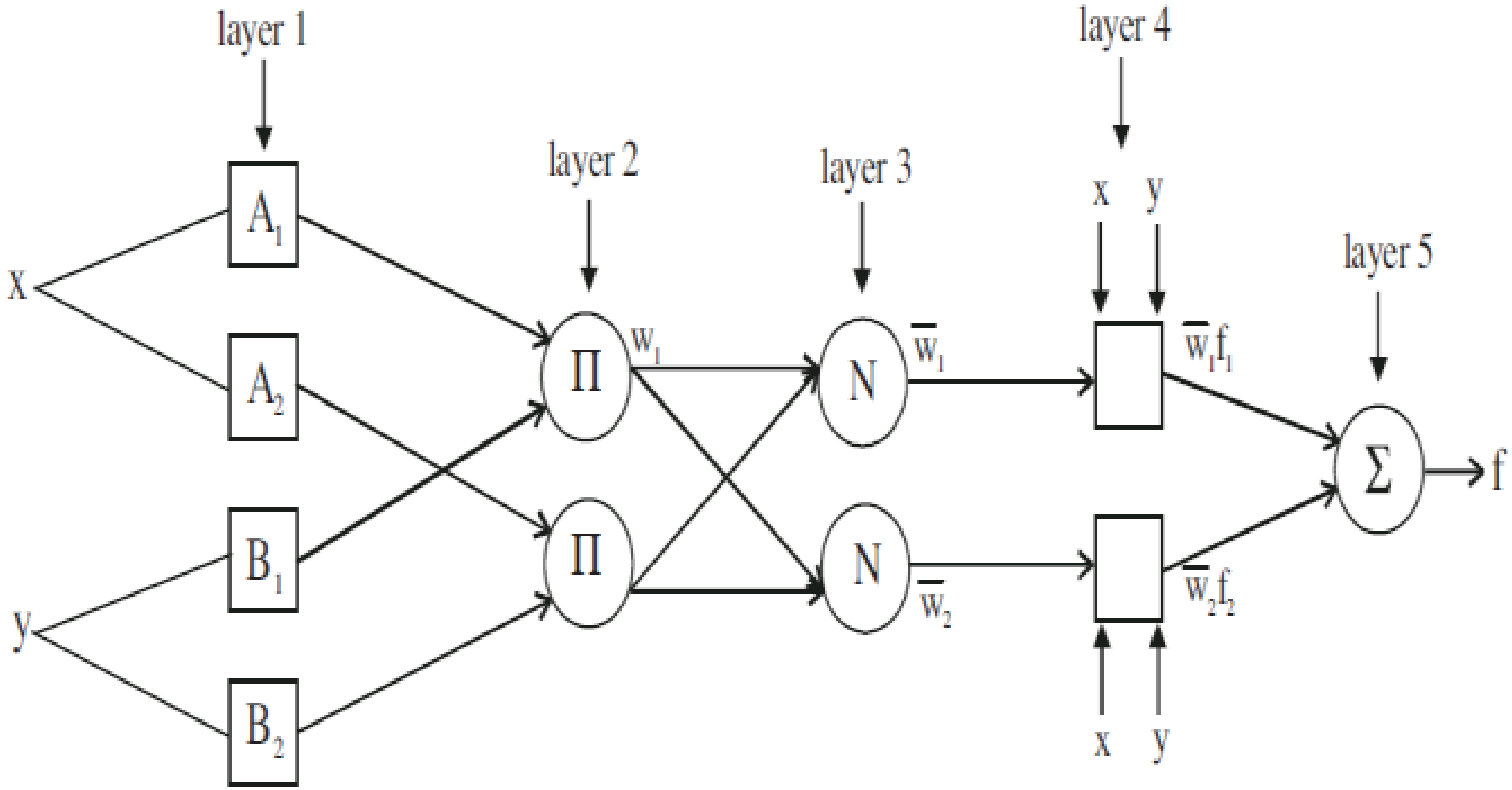
-adaptive Mamdani fuzzy logic PSS (AMFLPSS

----fixed centers FLPSS

(power 0.9 p.u., 0.9 pf lag)

Adaptive Neuro-Fuzzy Inference System

General Schematic of ANFIS



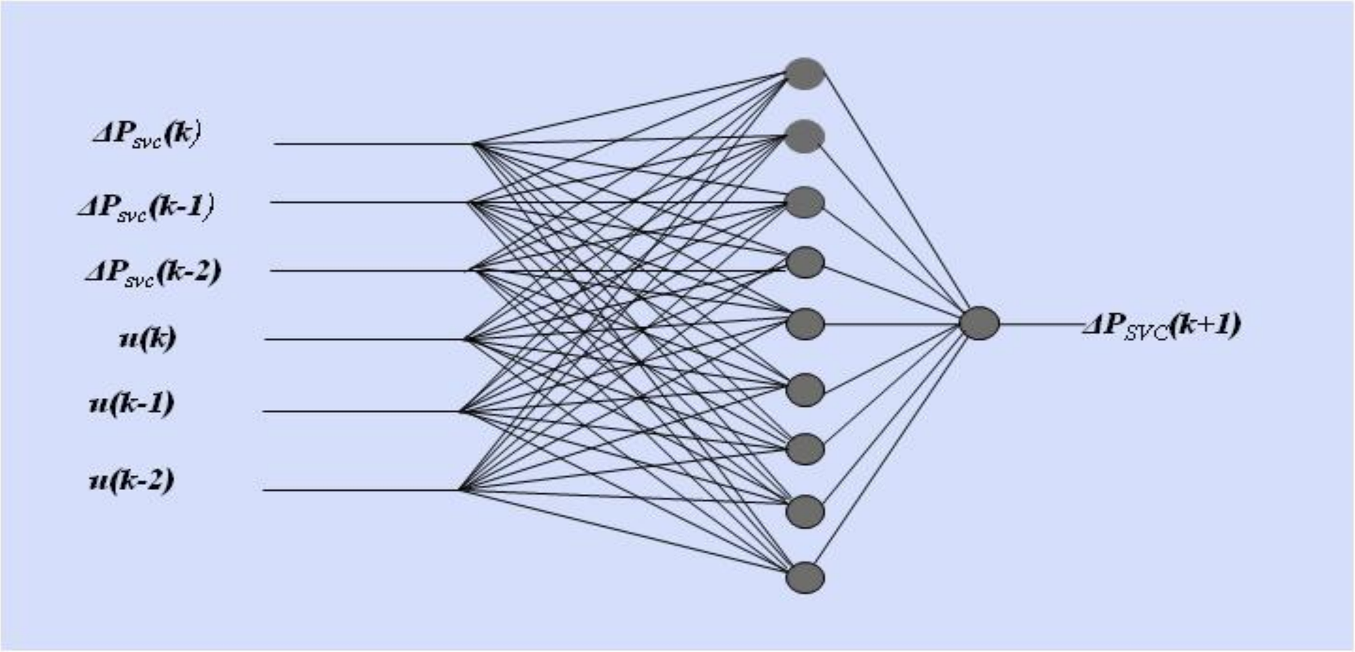
Basic structure of a typical ANFIS with two inputs and two-rule fuzzy system

Adaptive Neuro Fuzzy Inference System

- An ANFIS is an integration of neural networks and fuzzy inference systems to determine the parameters of the fuzzy system.
- Automatically realize the fuzzy system by using the neural network methods.
- Fuzzy Sugeno models are involved in the framework of adaptive system to facilitate learning and adaptation.
- Permit combination of numerical and linguistic data.
- Requires structural and parameter learning algorithms.

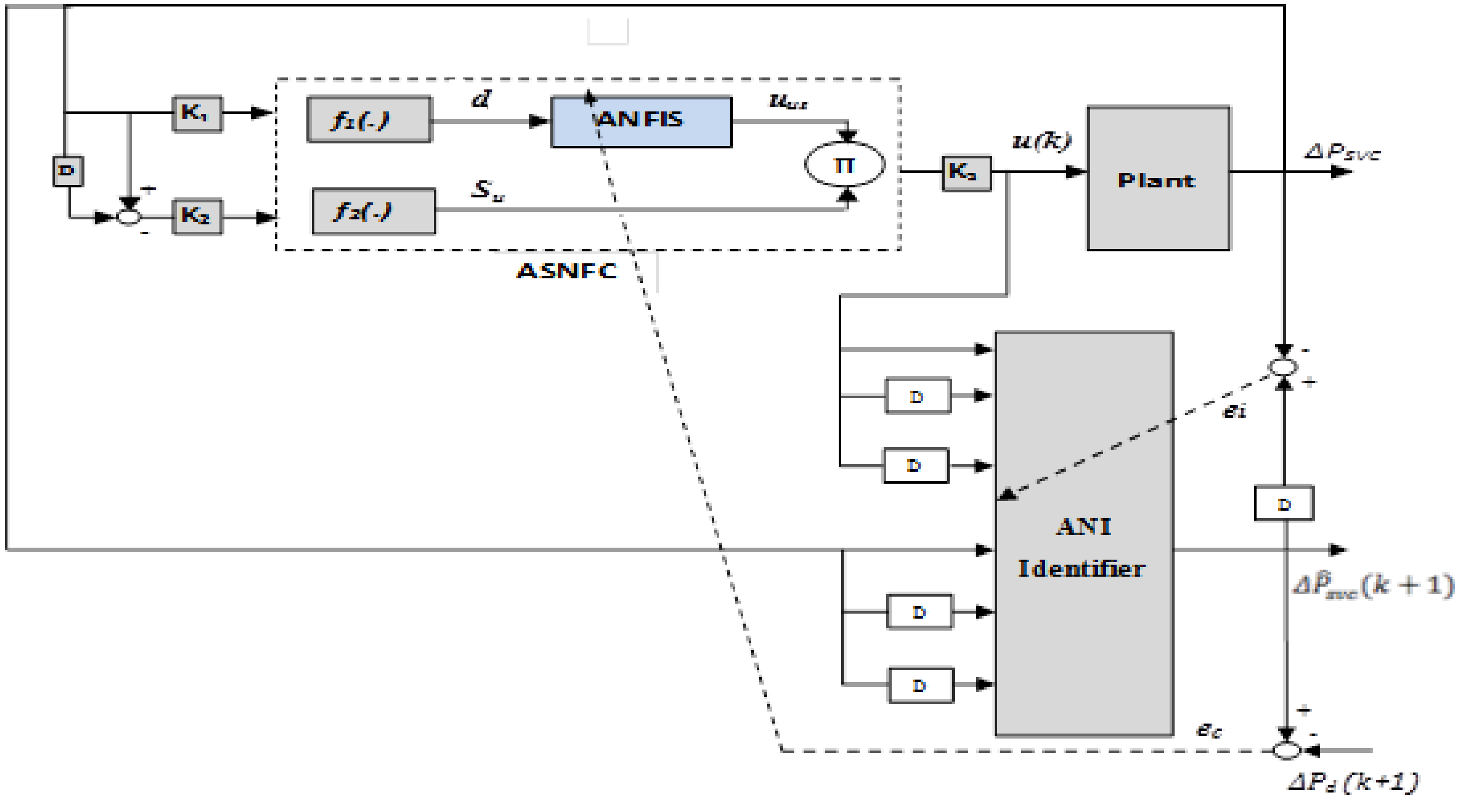
The Proposed Adaptive Neuro-Identifier

- A Multilayer Perceptron (MLP) network is constructed to represent the plant



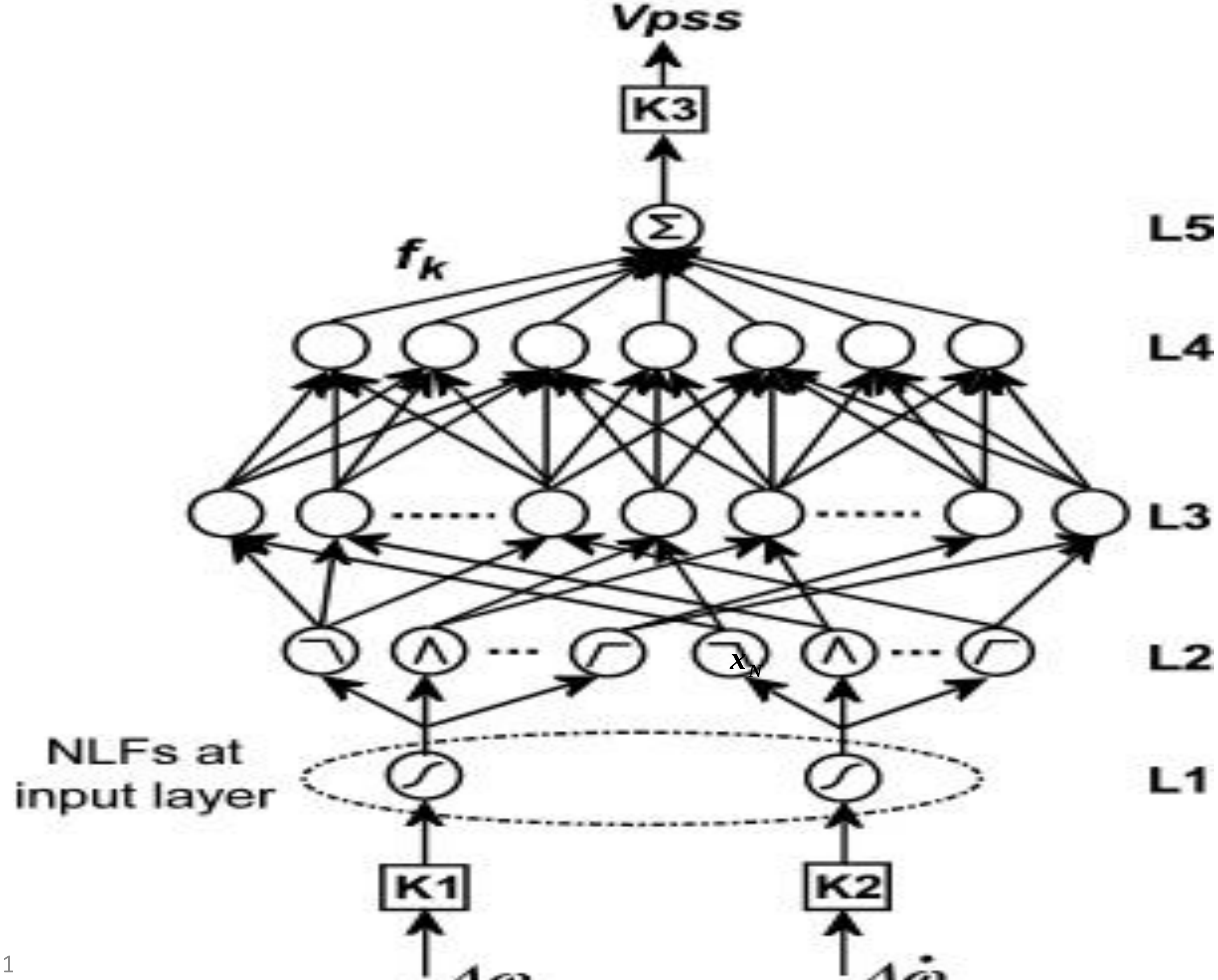
Architecture of adaptive neuro-identifier

Adaptive Simplified Neuro-Fuzzy Controller



Proposed control system structure

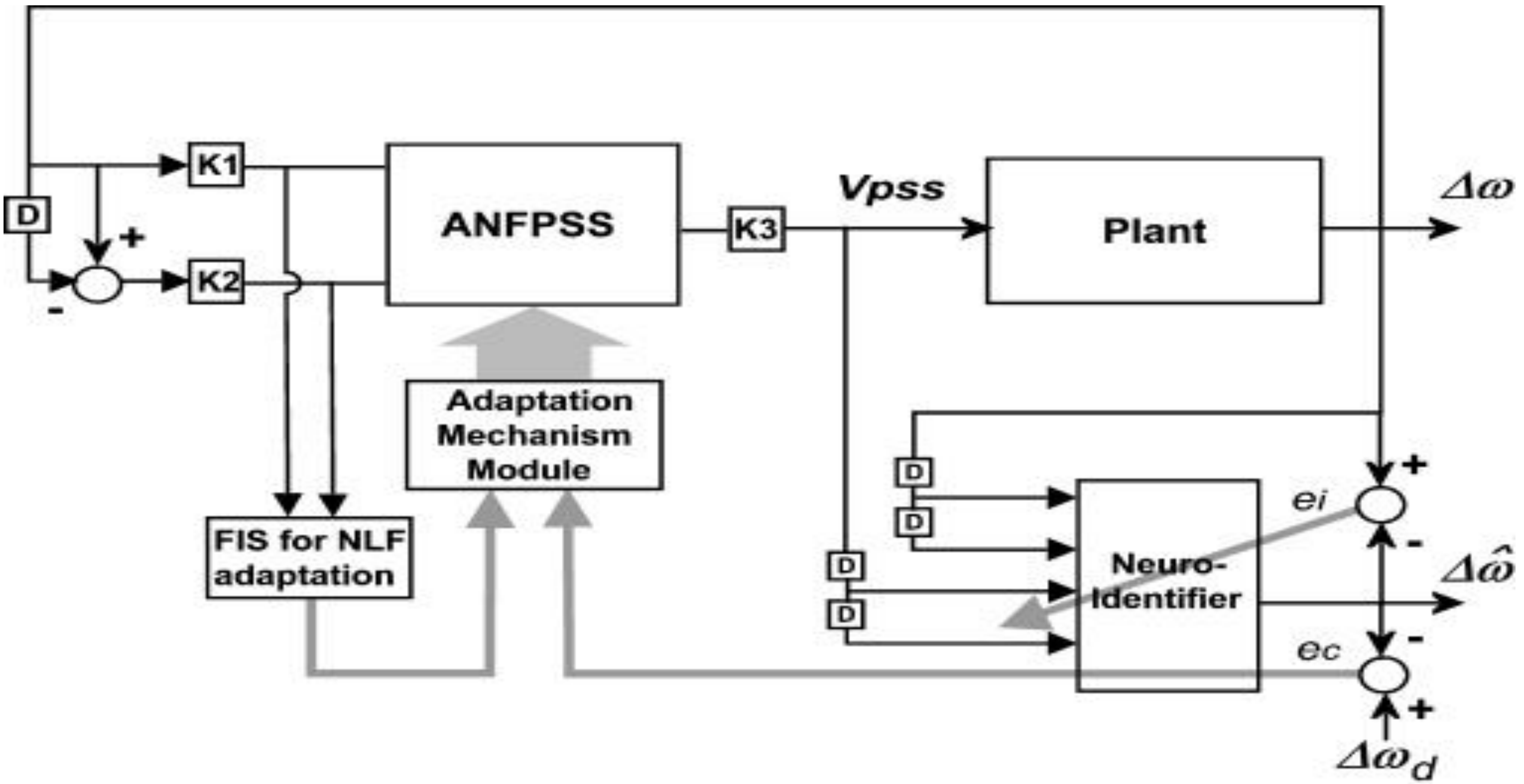
NFC architecture



Nonlinear Function (NLF):

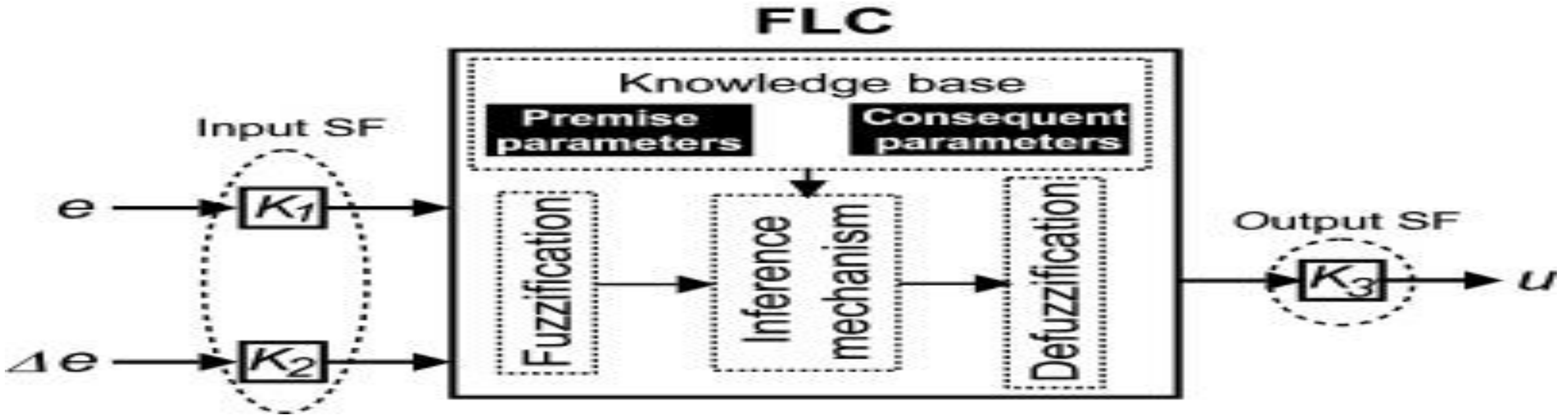
$$f(x_N) = sign(x_N) \cdot |x_N|^{\alpha}$$

Control system structure



Online Adaptive Neuro Fuzzy Controller for Nonlinear Functions in the Input Layer for Damping Power System Oscillations

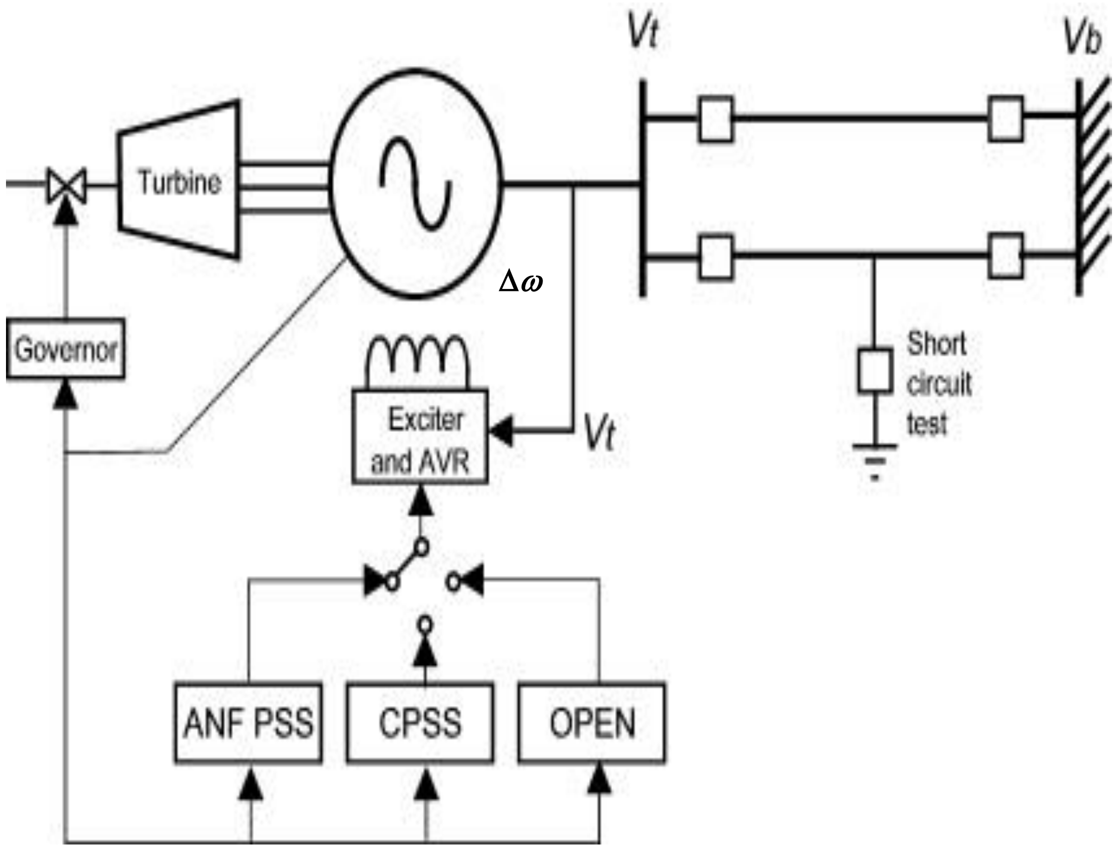
A fuzzy PSS is usually made adaptive by adjustment of input membership functions (premise) and consequent parameters (CPs).

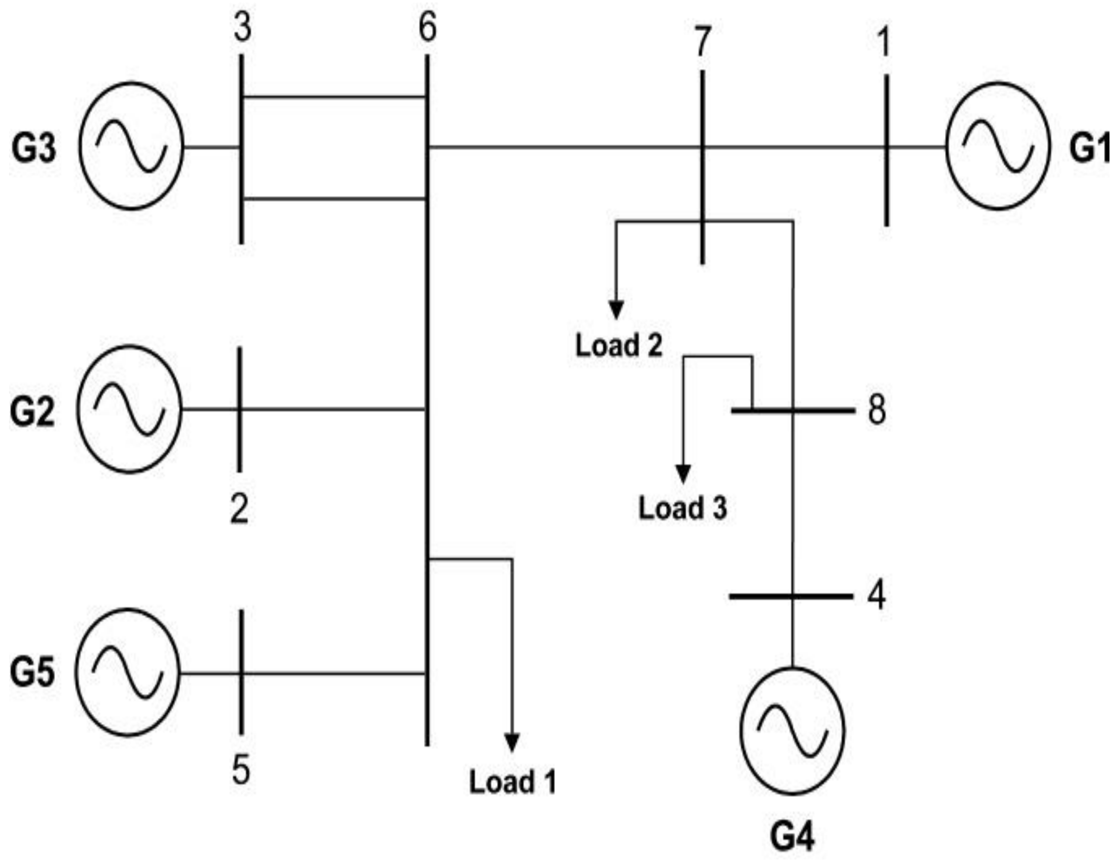


Number of controller parameters depend on the shape and number of membership functions.

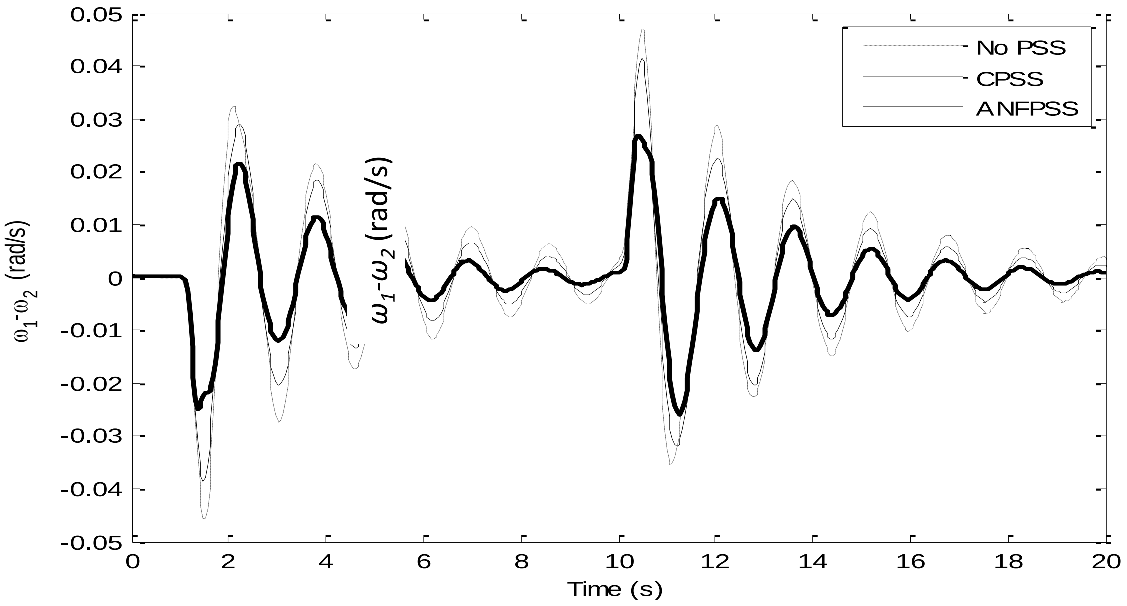
Scaling factors have received little attention in the adaptive fuzzy PSS design

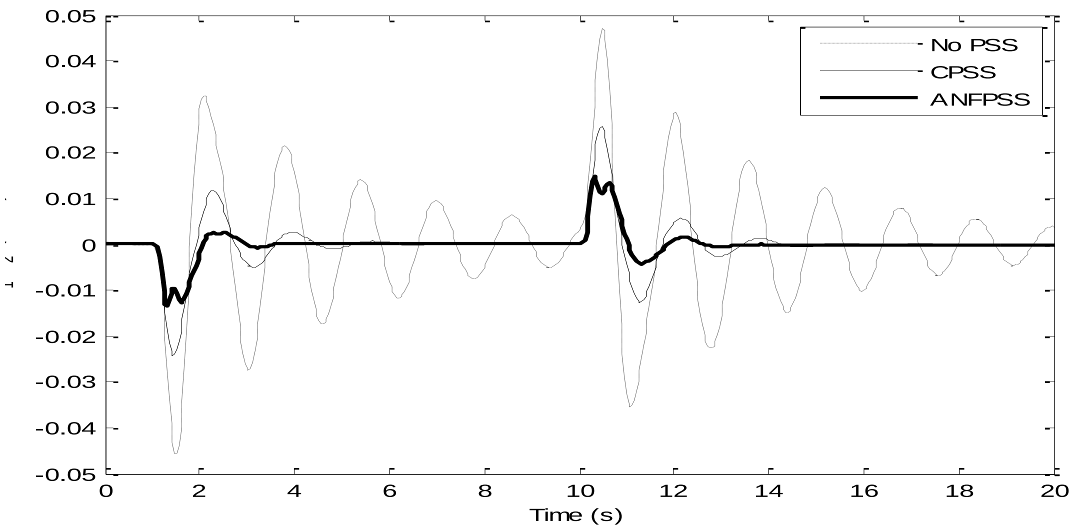
System Configuration

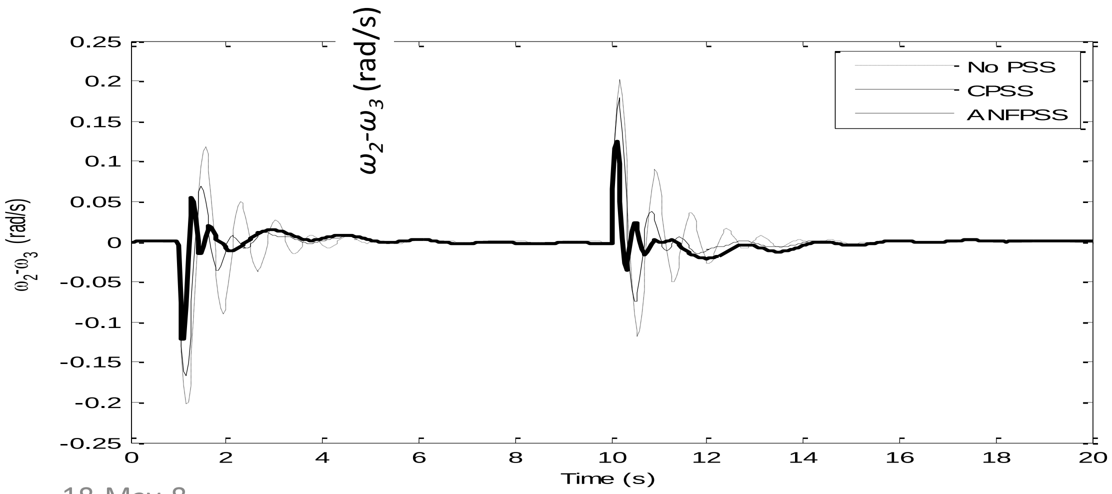




Simulation results Multi-machine power system.







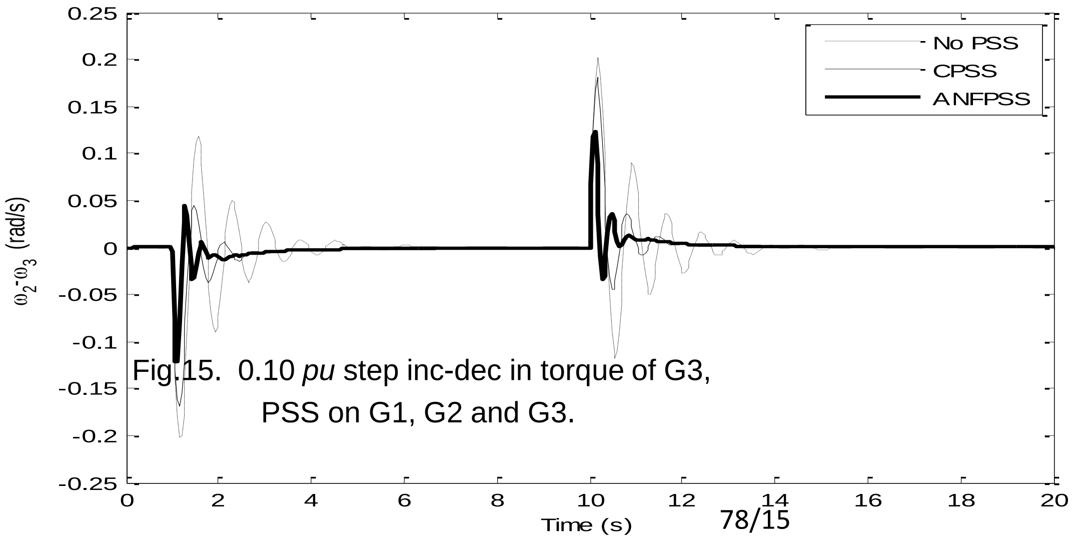


Fig.15. 0.10 *pu* step inc-dec in torque of G3, PSS on G1, G2 and G3.

1.5 MW VSWECS

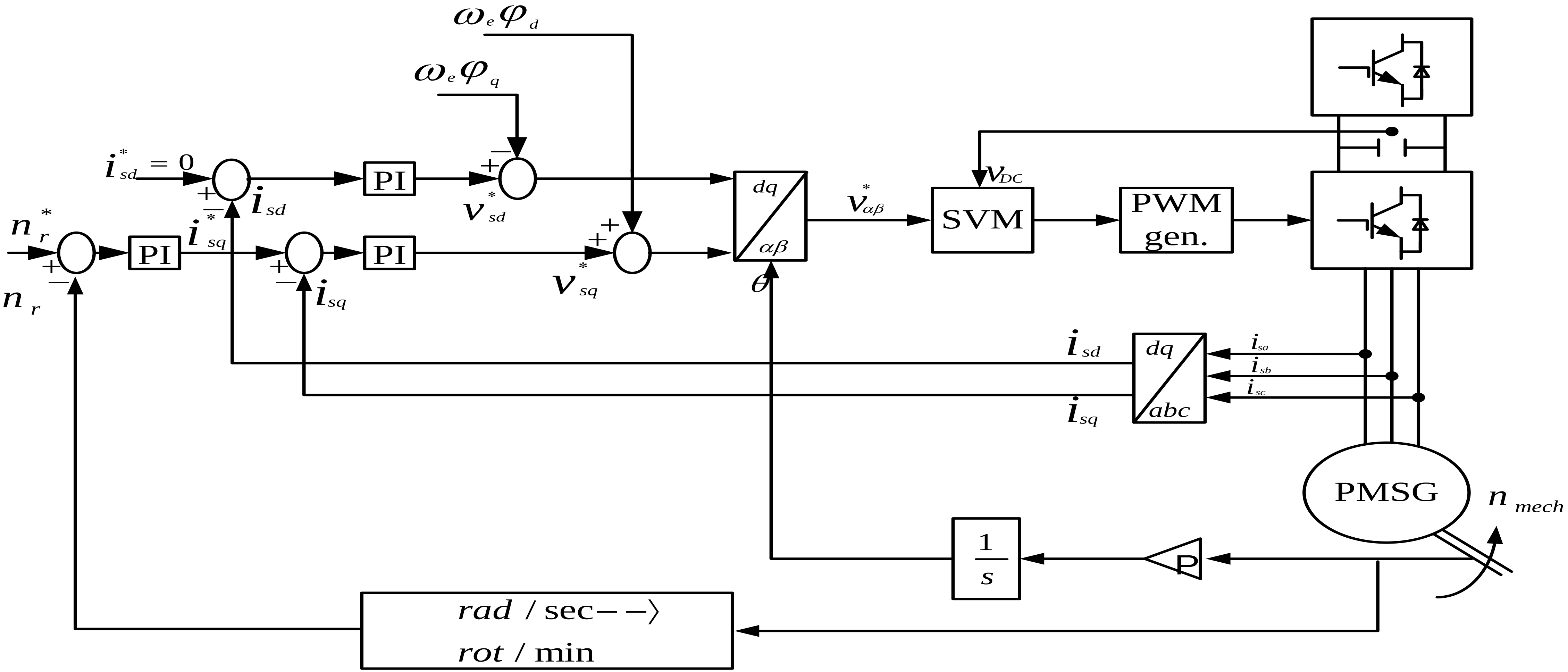
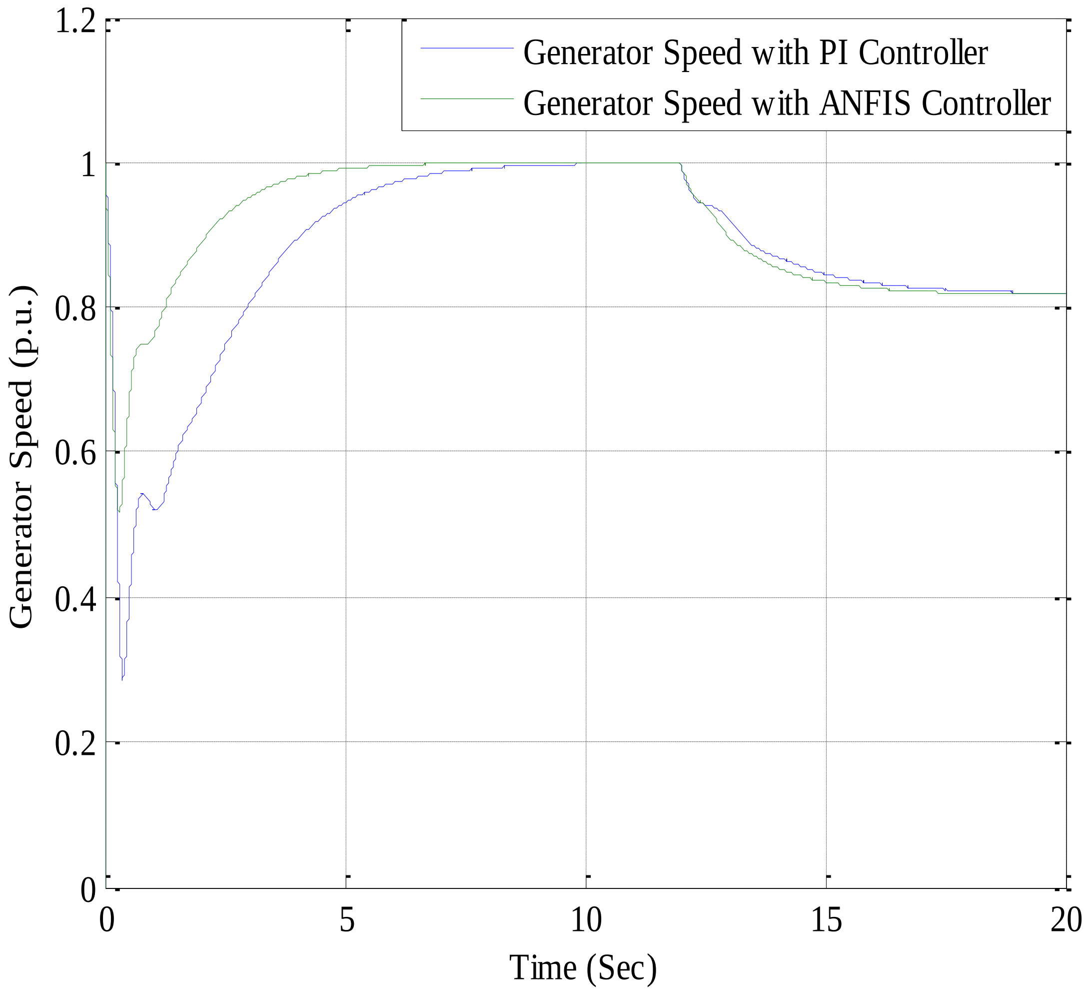
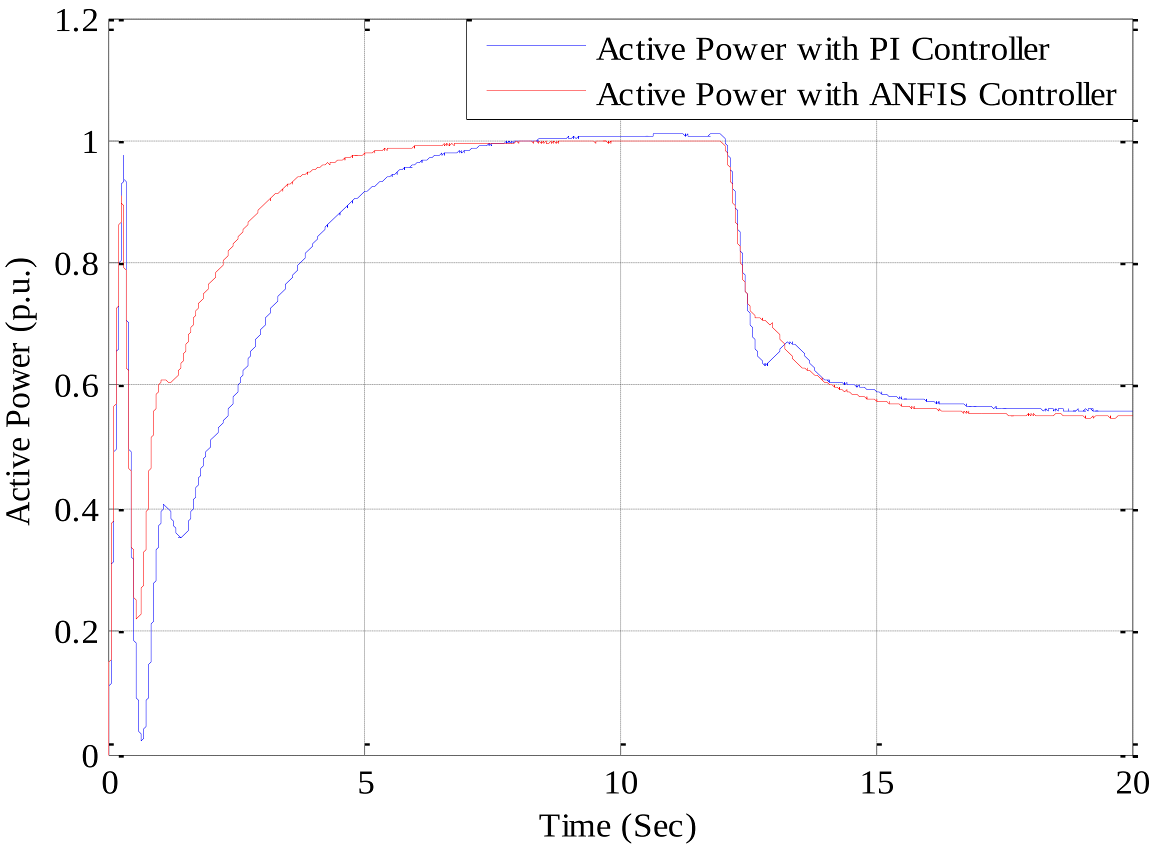


Fig.2 Field oriented control scheme with speed sensor at generator

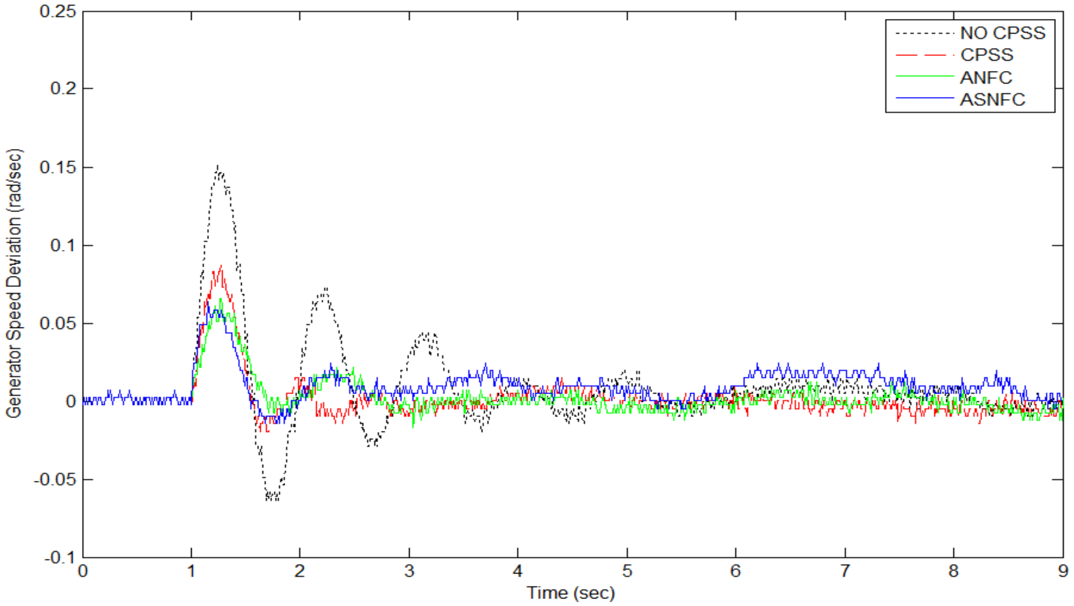
- Applied to the 1.5 MW wind turbine system.
- The wind speed starts at 11m/s, is changed to 9 m/s after 12 s



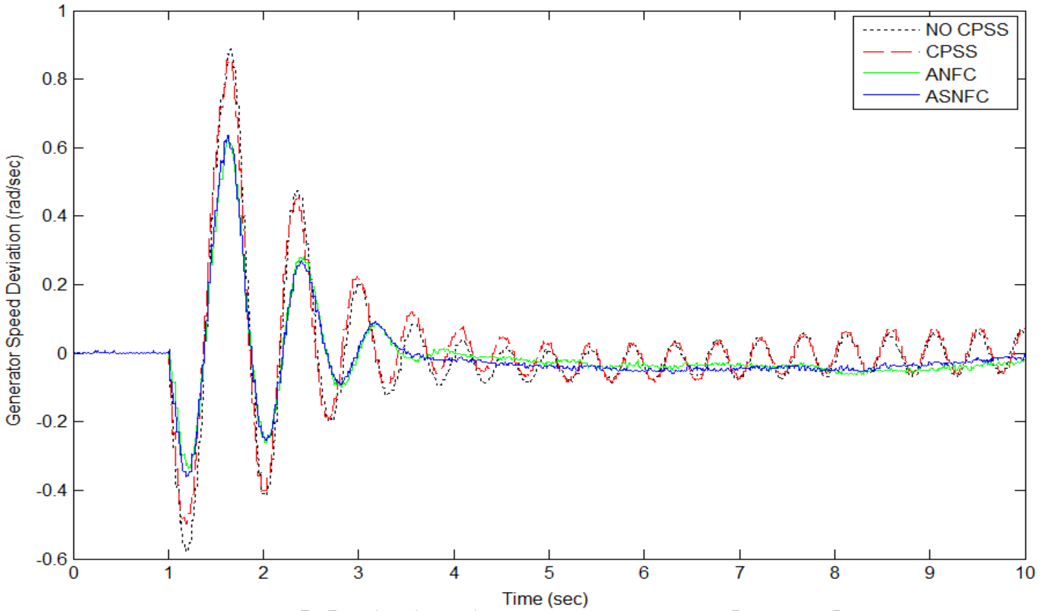


Experimental Results of Applying the ASNFC in a Real-Time System

200 km Transmission Lines



Generator speed deviation in response to a 15% step increase in the torque reference (P=0.80 p.u. and 0.75 p.f. lag)



Generator speed deviation in response to a three-phase to ground short circuit test at the middle of a 200 km transmission line with an unsuccessful re-closure (P=0.97 p.u. and 0.93 p.f. lag)

Concluding Remarks

- A wide spectrum of AI applications in power systems, from load forecast to maintenance, is being explored.
- A general survey of the type of AI applications that have been and are being explored for application in power system has been attempted.
- This is not an exhaustive survey and some other applications are also being pursued.
- Actual application of AI techniques, particularly for real-time applications, is lagging. One application that seems to have been adopted by the utilities is neural network based load forecast algorithms.

Thank you

Questions?

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