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Efficient Plant Supervision Strategy using NN Based Techniques

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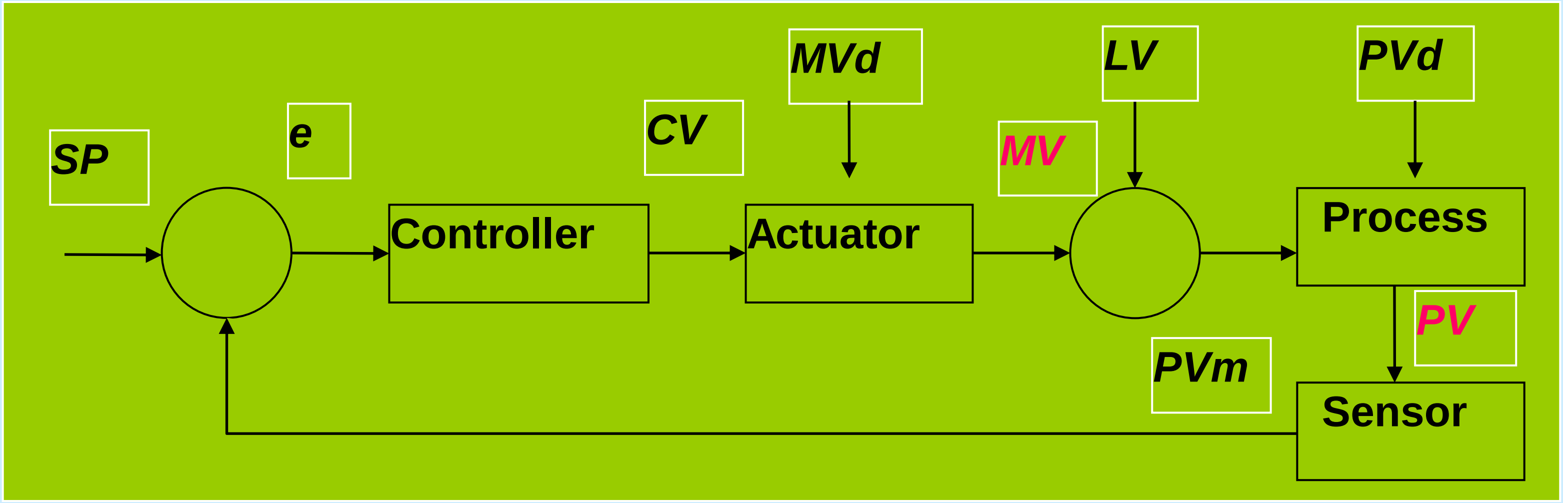
Summary

- Detect and isolate faults in sensors, actuators and process under steady state conditions
- Use of massive NN based functional approximation techniques.
- Use rule based techniques

The main problems encountered and Motivation

- Model based techniques doesn’t provide deterministic fault detection (FD) tasks.
- Lack of robustness due to disturbances.
- No deterministic fault isolation (FI) to discriminate sensors, actuators or process faults withowt redundancy

The Application Scenario: Conventional Control Loop Structure

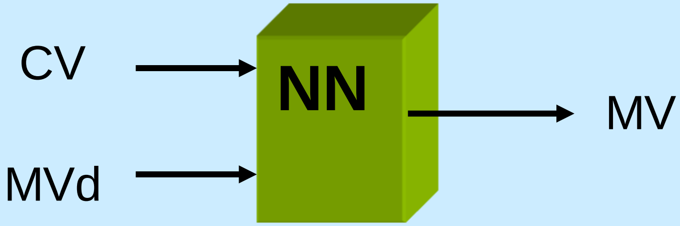


Block diagram of a generic feedback control loop

Recurrent Causality of feedback control loops

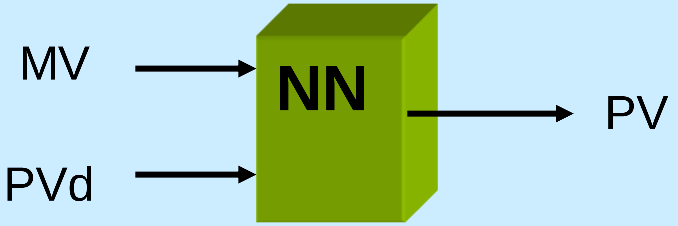
Manipulated variable

$$MV = f(CV, MVd)$$



Process variable

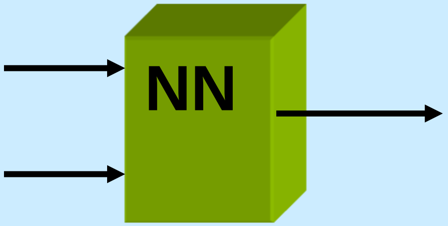
$$PV = f(MV, PVd)$$

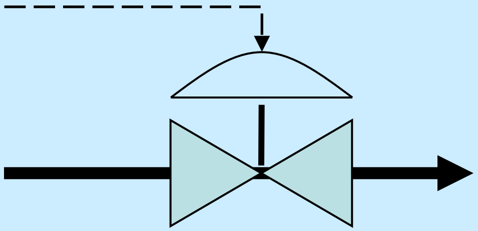


Recurrent Causality of feedback control loops

Servo-actuator

$$MV = f(CV, MVd)$$





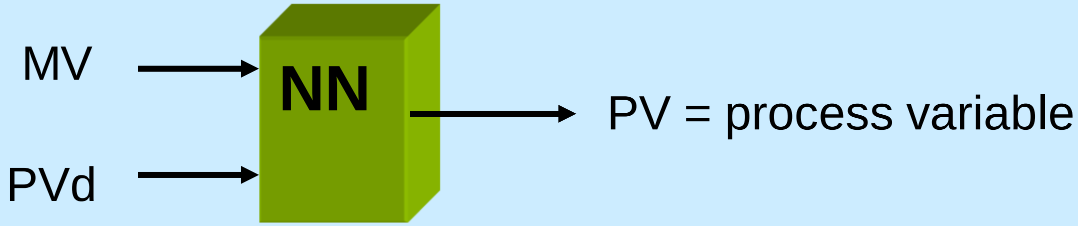
Recurrent Causality of feedback control loops

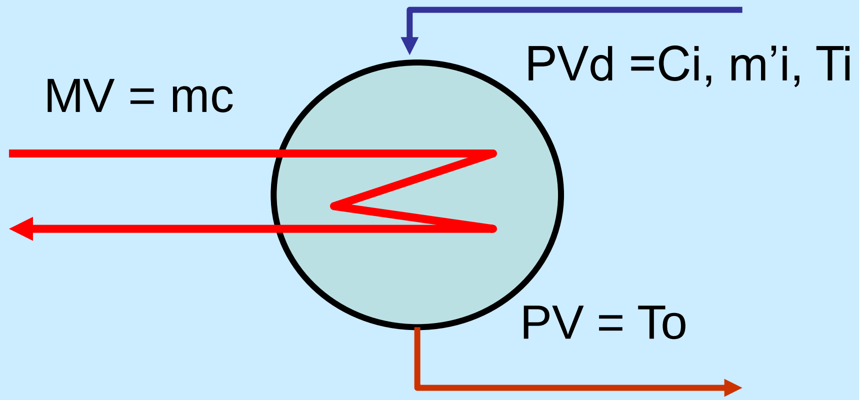
Controlled Process

$$PV = f(MV, PVd)$$

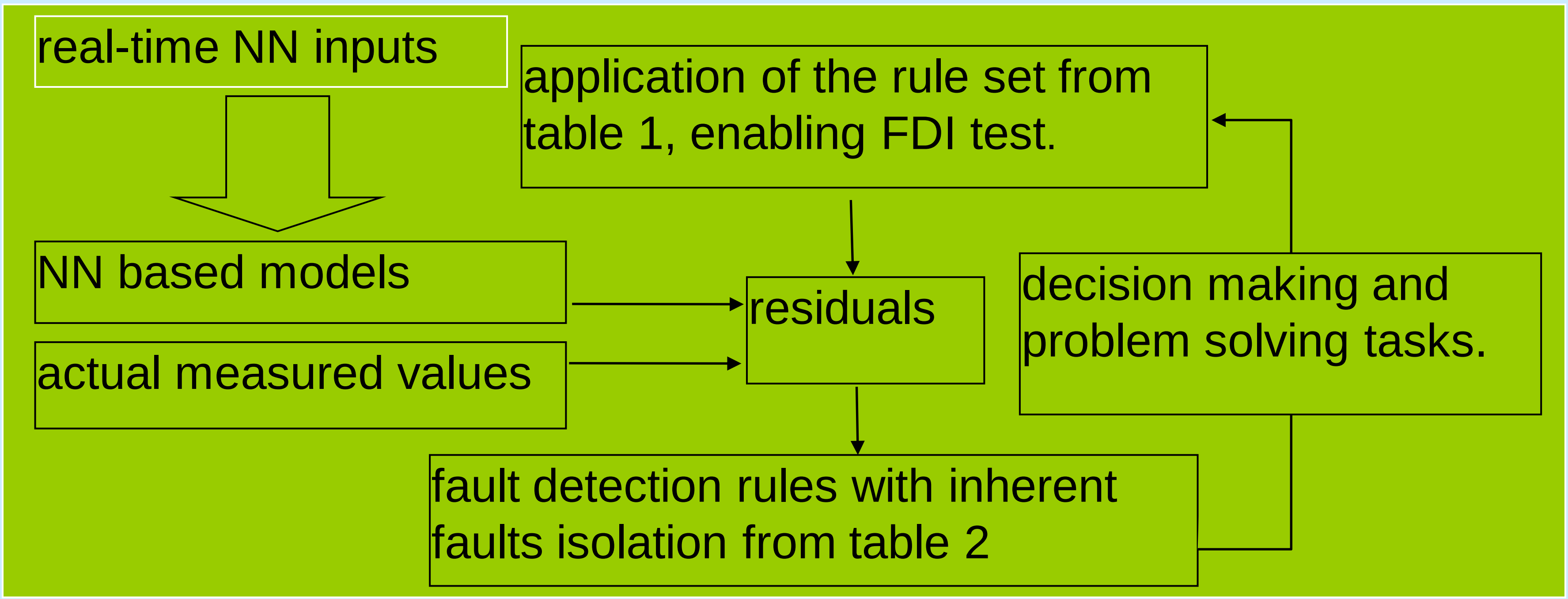
Manipulated variable

Process variable disturbance





Flowchart of the Supervision Scheduler



Consistence test to anable the supervision task

Steady state condition test

Preliminary set of rules to enable a supervision task		
Premise	Conclusion	
IF **e** < Te AND **de** < Tde	THEN	STE
IF **e** > Te AND **de** < Tde	THEN	OIR
IF **e** > Te AND **de** > Tde AND elapsed time > t_{MAX}.	THEN	OIR

e = control error
Te = error tolerance
Tde= error derivative tolerance or rate of change tolerance

STE = Supervision task anable
OIR = Operator Intervention required

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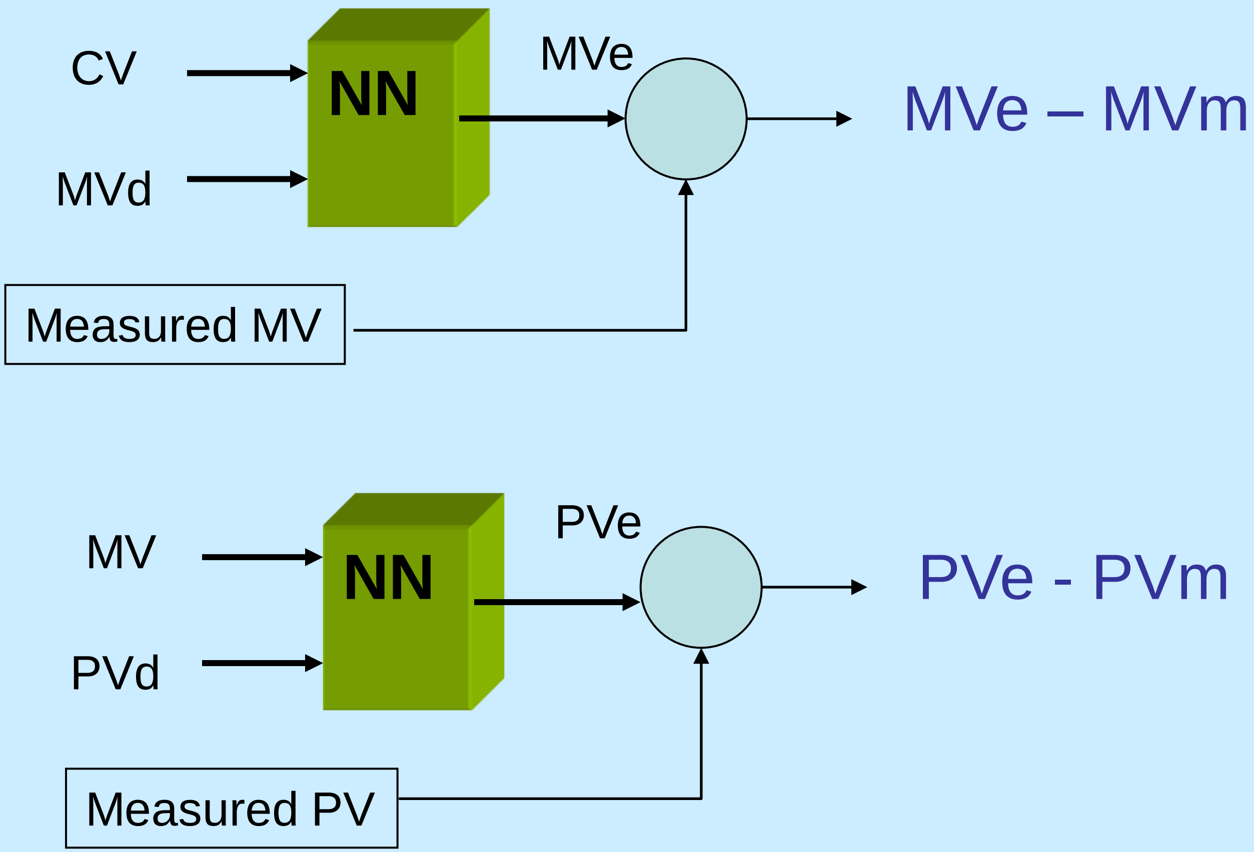
Residuals evaluation based supervision

Relevant Residuals
- MVe - MVm
- PVe - PVm



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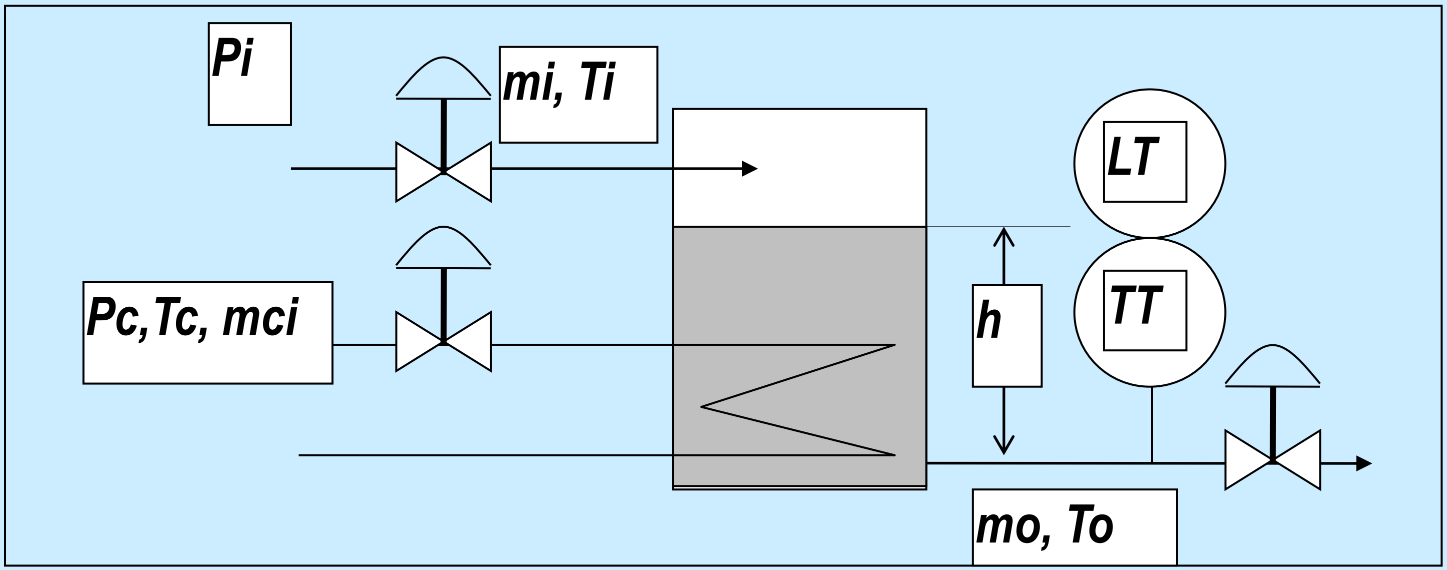
Residuals evaluation based supervision

Control Loop Device	Residual evaluation
Actuator test	**IF abs(MVe-MVm) < *Ta* THEN proceed, ELSE actuator fault**
Process test	**IF abs(PVe-PVm) < *Tp* THEN proceed, ELSE fault due to process parameter changes assumed.**
Sensor test	**IF abs(PVe-PVm) < *Ts* and process unchanged, THEN proceed, ELSE fault due to sensor drift assumed.**

Temperature and Level Process Scheme



Pilot Plant Layout

Inherent functional dependences on the pilot plant control loops

Feedback control loop variables	**Tank level**	**Heat Exchanger**
LV	f(mo)	f(Ti, mi, Tc)
MVd	f(Pi)	f(Pc)
PVd	f(h)	transf. coeff.

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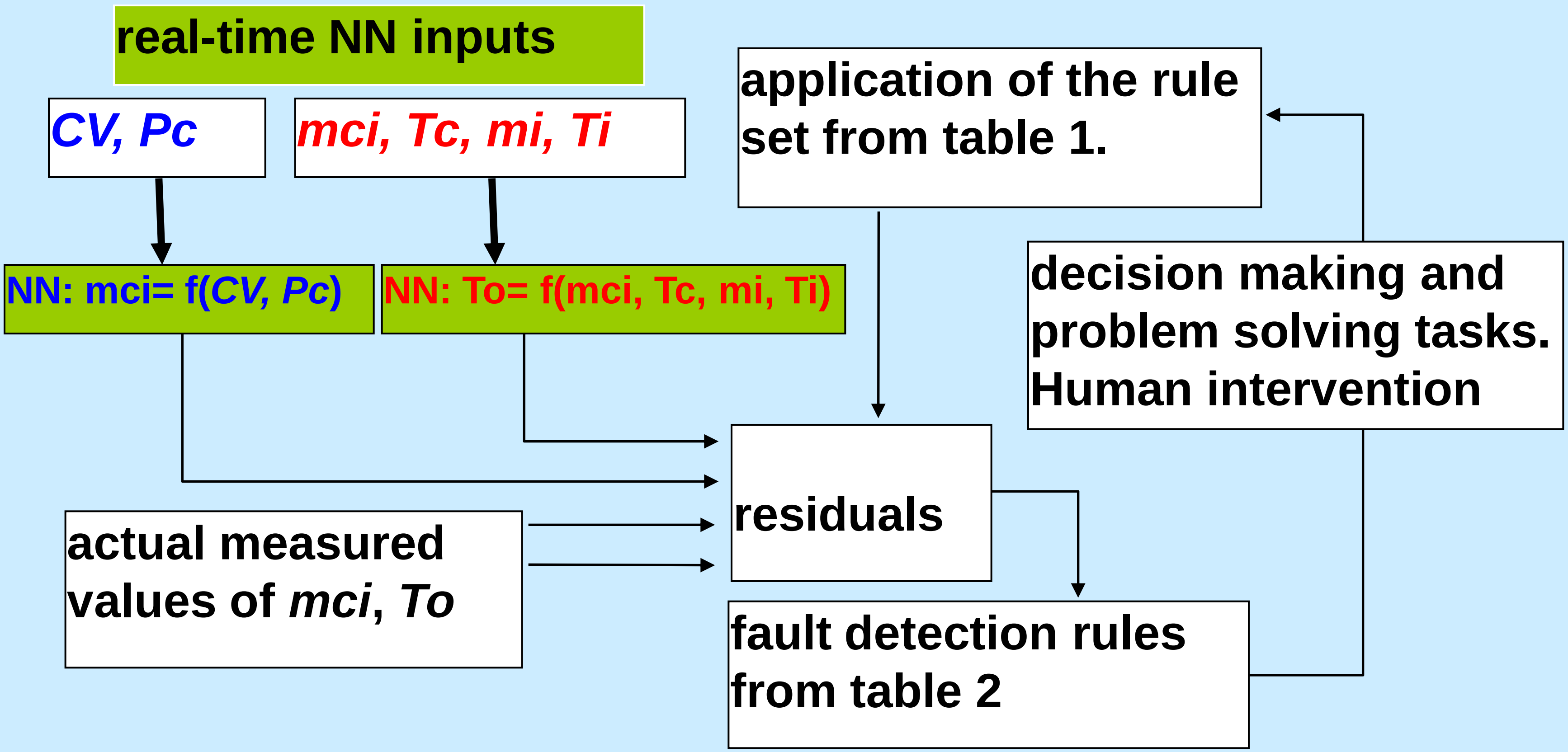
The NN based models included in control loops supervision structure

NN based functions applied on pilot plant	***Level control NN based models***	***Temp. control NN based models***
MV = f(CV, MVd)	**$Mi = MV = f(CV, Pi)$**	**$mci = MV = f(CV1, Pc)$**
PV = f(MV, PVd)	**$H = PV = f(mi, mo)$**	**$To = PV = f(mci, Tc, mi, Ti)$**

Supevision cycle scheduling



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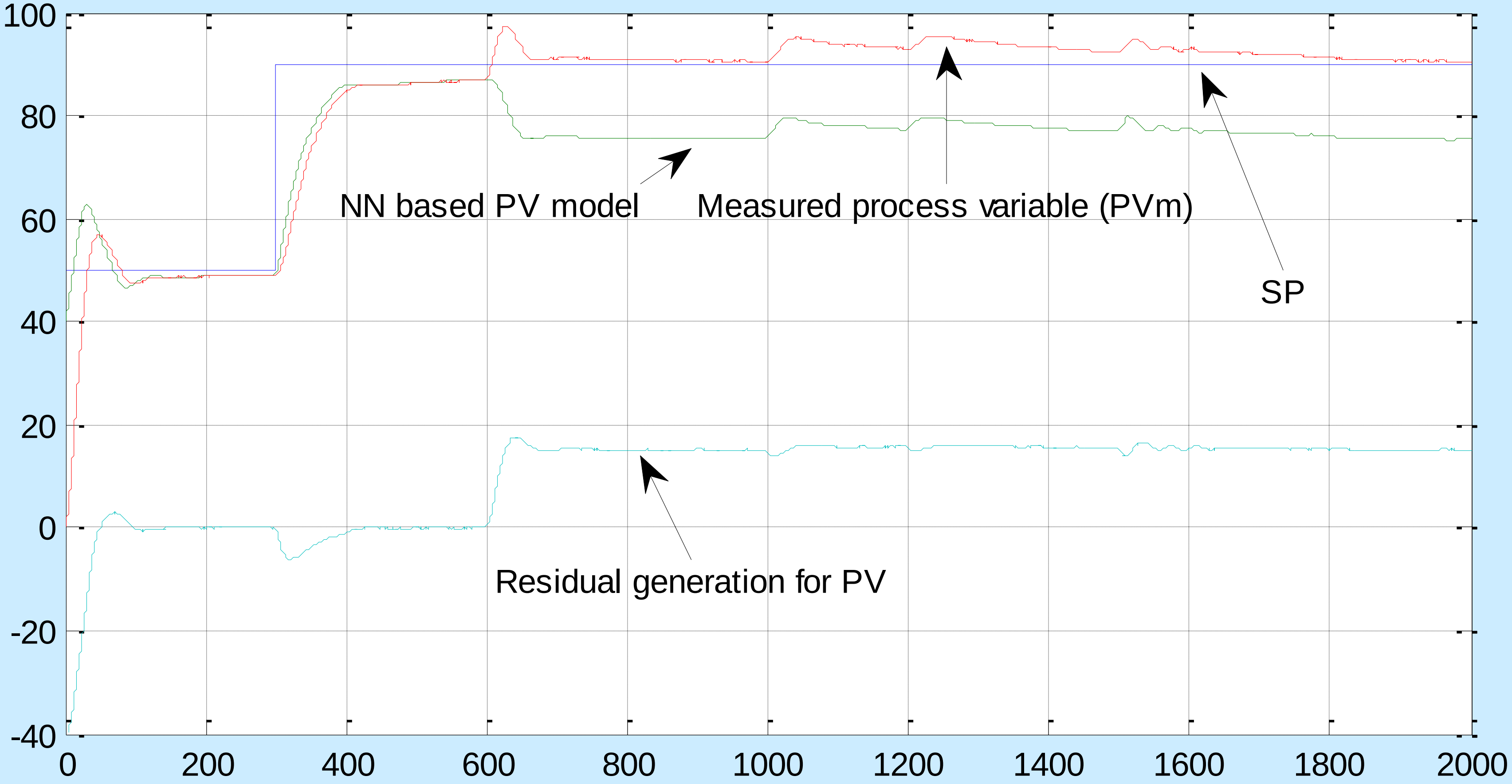
Some experimental results



Conclusions

A supervision strategy focused on the detection and isolation of plant faults in closed loop control systems under steady state conditions, on the basis of causal NN based modeling techniques has been proposed and successfully applied.

Accurate training data achieved

Since historical data is stored under steady state conditions, training data is accurately achieved.

Detection of sensor drift faults

Results show that the detection of a drift fault associated to the process variable (temperature) measuring sensor has been successfully achieved under the condition of a correct measuring system.

Detection is not sensible to process disurbances

The detection of a drift fault associated to the process variable (temperature) is not sensible to process disturbances. Such a characteristic is very interesting from the point of view of robustness and system reliability.

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Disadvantages

Updating estimator dynamics

This supervising system needs to be updated every time parameter changes are detected, by training the applied neural networks. This characteristic is a serious drawback since the plant must be forced to an off-line condition, which affects the productivity.

Doesn't work when in transient state modes (load changes, disturbances, abrupt parameter changes)

The most important disadvantage of the applied methodology is the impossibility to detect faults when the process is under transient state.

Your presence is appreciated

Matlab-Simulink NN training commands.

Action	Command
Net initialization	Net = init(net);
Feedforward NN structure and Training algorithm CGF =(Conjugate Gradient Fletcher)	Net = newff(minmax(p),[15,10,1], {‘tansig','tansig','purelin'},'traincgf');
Results display	net.trainParam.show = 5;
Training epochs	net.trainParam.epochs=300;
Training command	[net,tr]=train(net,p,t);
NN simulink structure	gensim(net,-1);
Training results	TRAINCGF-srchcha-calcgrad, Epoch 118/300, MSE 1.76e-8/0, Gradient 0.000194/1e-6

DeltaV Neural

Is a toolbox of the DeltaV software used to create and automatically train a NN.

Such trained is being applied to provide a continuous estimate of a measurement. (Virtual sensors).

This NN has been currently determined using lab test or a sample analyzer.

Historical data

is automatically collected on the upstream inputs that
we can identify as **potentially influencing** the sample measurement

The inputs that are most significant are automatically identified and then used in the training of the NN.

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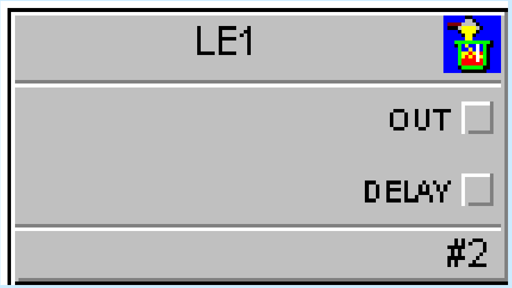
When we are modeling a process that uses lab analysis data, we use a Lab Entry (LE) function block.

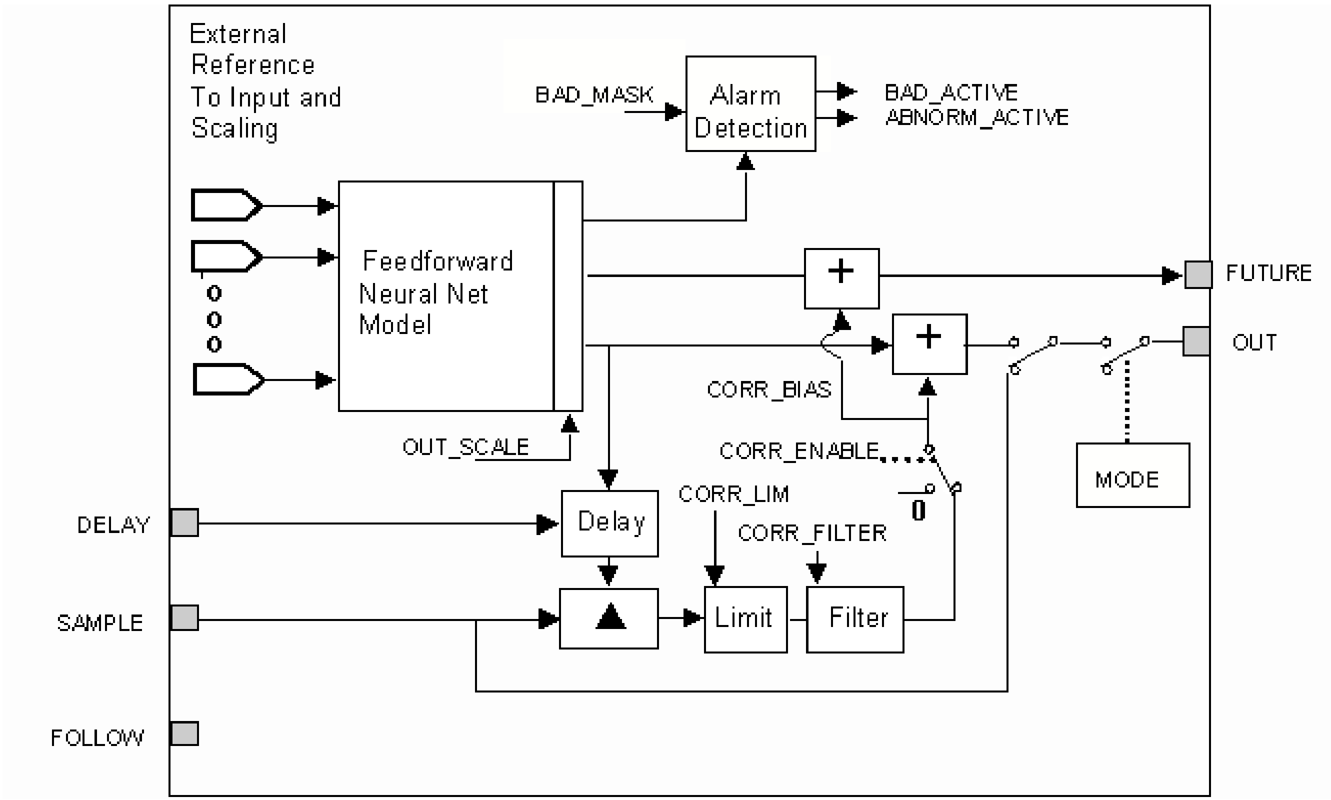


Through the configuration of the NN function block, we may specify the upstream measurements that we believe influence the estimated sampled parameter

The diagram shows the internal components of the Neural Network function block

Schematic Diagram - Neural Network Function Block

The following diagram shows the internal components of the Neural Network function block:



Neural Network Function Block Schematic Diagram

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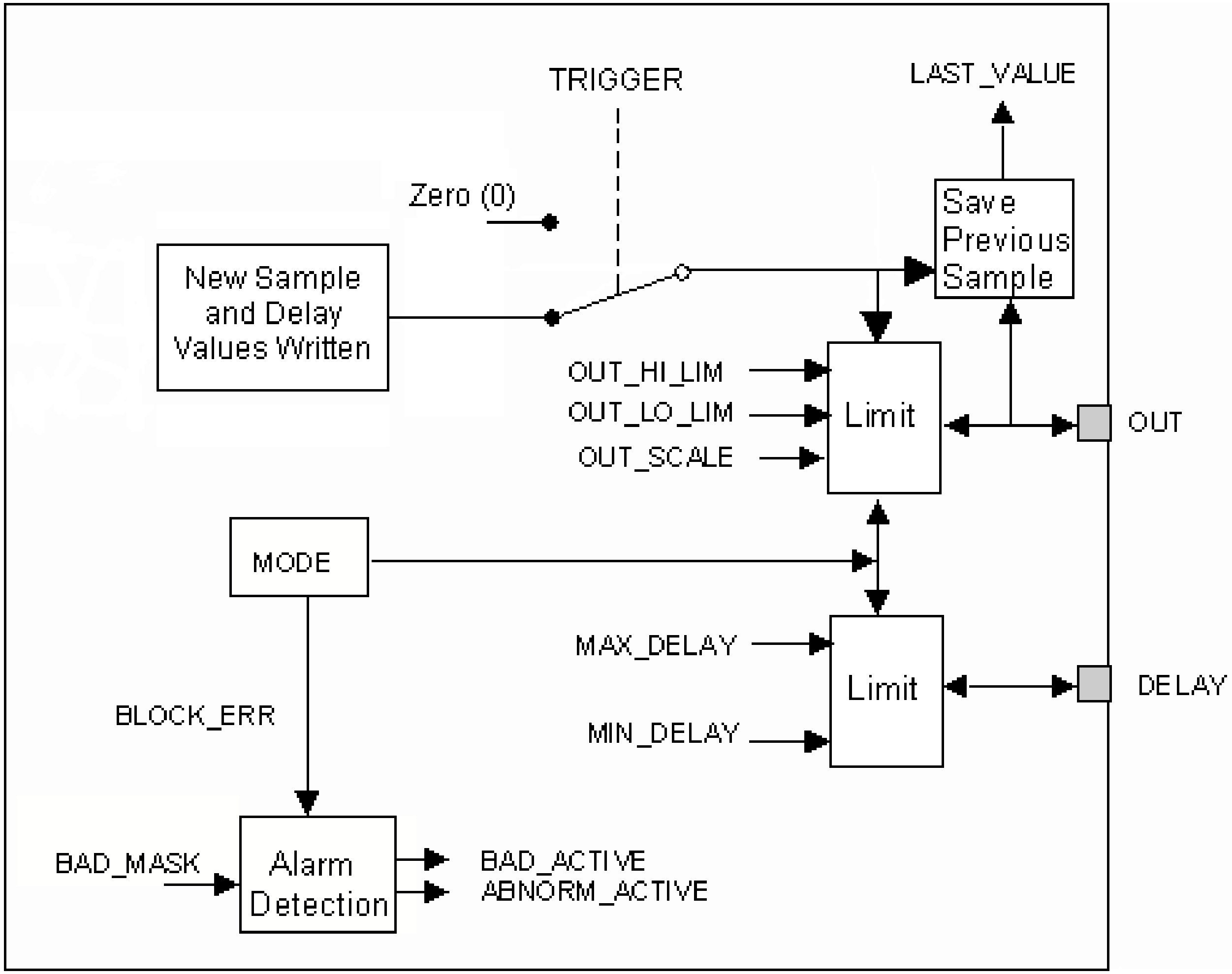
Schematic Diagram - Lab Entry Function Block

The following diagram shows the internal components of the Lab Entry function block:



Lab Entry Function Block Schematic Diagram