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Developing ANN based Virtual / Soft Sensors for Industrial Problems

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Abstract: This paper briefly reports experience of our research group in developing and deploying some promising approaches for virtual and soft sensing of crucial parameters for use in control systems of a process or plant. It briefs on the constraints and limitations of the measurement of crucial parameters by physical means and hence the need and viability to go for virtual/soft sensing.. The approaches used are variants of Artificial Neural Network topologies and their supervised and partly supervised training algorithms. The paper provides a brief overview of the virtual sensor development based on these approaches for selected process situations and provides validation results to justify the approaches used. The industry sectors for which these solutions were developed are automotive, cement grinding process and kiln process, and chemical process for pH control. Some of these approaches have been implemented in the industry underlining the significant role the virtual/soft sensing mechanisms could play in process operations.

Keywords: virtual sensing, soft sensing, artificial neural networks, wavelets, wavenets

1. INTRODUCTION

Increasing global competition poses a challenge of optimizing the various process/plant operations in the industry. The process optimizers usually help in optimizing economic objectives, such as consumption of energy, raw materials, utility etc. For process optimization, it is usually required to operate the process at operational and quality constraints, which requires tighter quality control.

To achieve tighter quality control, it is necessary to have online feedback of the crucial quality parameters. Though online sensors are available for many of the physical variables involved in the process e.g. temperature, pressure, flow, velocity, displacement, etc., reliable and accurate online sensors for the quality variables are scarce, too costly, or sometimes less reliable. The quality control is often dependent on the offline laboratory measurements or special test measurements using methods that are tedious and time consuming. When these measurements are made less frequently (say at hourly or bihourly rate), tighter quality control becomes difficult to achieve. S*oft-sensors* or the *virtual sensors* find their application in such scenarios to meet this challenge. We define soft sensors as models that make use of less-frequently available measurement values of quality parameter they soft-sense and the virtual sensors as models which estimate it making use of other relevant plant/process measurables available economically and conveniently. The following sections describe such implementations of the soft/virtual sensors which were carried out by group of researchers (Kamat *et. al.,* 2005, 2006) in the stated processes/plants. The structures attempted are RNN (Recurrent Neural Network) and WNN (Wavenet Neural Network) which address the slower and faster dynamics respectively in the underlying process along with the nonlinear behaviour.

2. VIRTUAL SENSING IN VEHICLE POWERTRAIN

Wide band air-fuel ratio sensor (WAFR) is one of the critical sensors mounted on SI engines in an automotive. It serves as the sensor part in the feedback path of the closed loop lambda (normalized AFR) control that ensures the quality of combustion and hence the emission levels. However, the sensor has its limitations such as its operating temperature for reliable feedback value, operational life and reliability of its characteristics over its operational life (Prokhov *et. al.,* 2005). In the case of its substantial degradation or complete failure the closed loop control build around the sensor deprives of the feedback and switches over open loop mode thus causing somewhat inferior lambda control and hence the emissions. The virtual sensor steps in this situation to make the lambda value available for the control loop and the vehicle can drive, though compromised on quality a little, to the service station to get the sensor replaced. The virtual sensor running in parallel with the hardware sensor provides the analytical redundancy to monitor health of the hardware sensor and also complement it to refine the lambda control.

2.1 RNN for sensing lambda

For this application Recurrent Neural Network was the preferred choice over TDNN(Time Delayed Neural Network)

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to capture the nonlinear dynamic character of the lambda phenomenon. A virtual sensor (Kamat *et. al.,* 2006) is designed making use of the other sensed parameters/ actuation parameters at every engine event (control move deployment instant), namely, throttle position (TPS), engine rpm (RPM), manifold absolute pressure (MAP), manifold air flow (MAF), engine coolant temperature(ECT), fuel pulse width (FPW) calculated within control unit as shown in the figure 1. These variables are chosen based on our understanding of the key variables affecting the dynamics of the system.

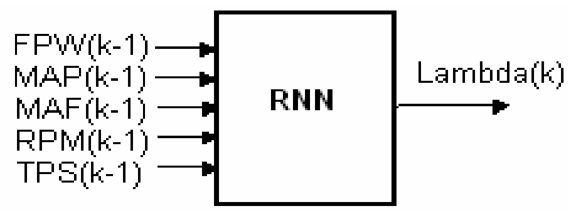

Fig. 1. RNN virtual sensor topology

The recurrent neural network topology devised is equivalent to a non-linear state-space model that maps inputs and outputs. The hidden neurons are equivalent to the states. However, the number of neurons could be more than the number of states. The output of the hidden layer is fed back to itself via a bank of unit delays. The dynamic behaviour of the model is given by a pair of coupled equations similar to linear state-space model (Haykin, 1999) as:

$$x(k) = f(x(k-1), u(k-1), Wxx, Wxu, Wxb);$$
$$y(k) = g(x(k)) = Cx(k); \qquad \ldots(1)$$

where, f is a nonlinear tansigmoidal function vector characterizing the hidden layer and C is the vector of synaptic weights characterizing the output . The output is tapped at the output node, which itself is the one of the nodes of the hidden layer (Fig. 2). The training algorithm adopted is based on the algorithm developed by Williams and Zipser (Williams, et. al.) and popularly known as RTRL (Real Time Recurrent Learning).

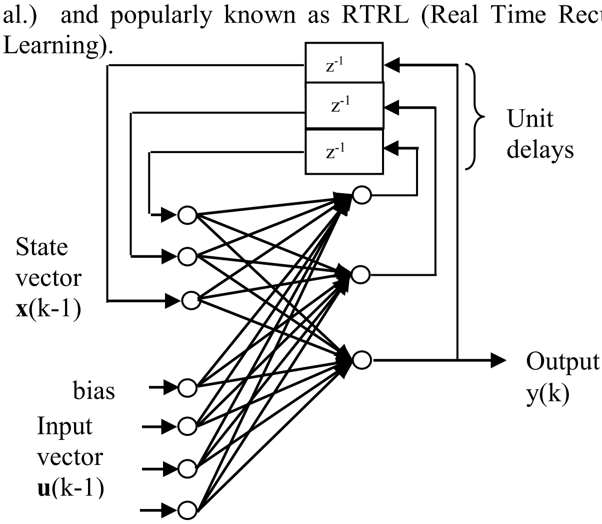

Fig. 2. RNN virtual sensor topology

The weights of a fully connected recurrent network are adjusted in real time using either a supervised continuous or a batch learning. The learning algorithm is an approximate gradient descent type that minimizes objective function of NMSE (Normalized Mean Squared Error), E_{Total} (batch type learning)

$$E_{Total} = \sum \frac{1}{2} e(k)^T e(k)) \qquad \ldots(2)$$

$$e(k) = \mathrm{d}(k) - y(k)) = d(k) - Cx(k) \qquad \ldots(3)$$

where, d is target vector and C is [1 0 0…] for a MISO system.

Using steepest gradient method, the increments in the weight matrix Δw at any instant k is given by

$$\Delta w(k) = -\eta \frac{\partial E_{Total}(k)}{\partial w(k)} \qquad \ldots(4)$$

where, η is learning rate of sufficiently small value.
The output is updated by

$$x_i(n) = \phi(w_{ix}^T x(n-1) + w_{iu}^T u(n-1) + w_{ib}^T xb) \qquad i = 1 \ldots N$$
$$y(n) = Cx(n) \qquad \ldots(5)$$

The lower bound of the number of nodes in the hidden layer is dependent on the system dynamics. In the actual implementation the nodes chosen were in the range 5-35. After extensive trials a 14 node hidden layer was found adequate. The sensor model is trained using the test bed data from a chosen widely followed American drive cycle as well as specially designed drive pattern which included open loop and closed loop response data with detuned and tightly tuned controller and special test data at two select gears (Kamat et. al., 2006 (2)). Event based samples were used in preference to time based samples to correspond closer to the engine operation at all operating conditions. A two step approach has been followed for training with an initial training of forward path of RNN followed by a training of the full RNN with feedback links restored. The figure 3 shows results for such a pattern where the lambda signal has comparatively low and high band widths respectively.

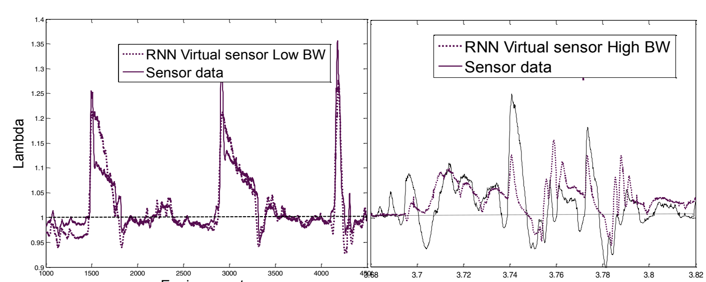

Fig. 3. Lambda : Sensor and RNN virtual sensor outputs (low and high bandwidth signals)

In similar manner the RNN virtual sensing was performed for the parameters, Manifold Absolute Pressure (inputs: TPS, RPM, MAF, FPW), Manifold Air Flow (inputs: TPS, RPM,