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Parameter Based Kalman Filter Training in Neural Network

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Abstract: Neural Networks (NNs) have been employed in many applications in recent years. A neural network is an interconnection of a number of artificial neurons that simulate a biological brain system. It has the ability to approximate nonlinear functions and can achieve higher degree of fault tolerance. NNs have been successfully introduced into power electronics circuits where a NN replaced a large and memory demanding look-up table to generate the switching angles. The neural network controllers for engine idle speed and Air/Fuel (A/F) ratio control produce signals that affect the operation of the engine while the neural network models are used to describe various aspects of engine operation as a function of measurable engine outputs. This study aims to study the behavior of the parameter based kalman filtering in neural network.

Key words: KF-kalman filtering, neural networks, NNs, brain, fault

INTRODUCTION

The proposed Neural Network (NN) controller has 5-3-1 structure (five inputs, three nodes in the hidden layer and one output node). The nodes on the hidden layer have sigmoid transfer function and the output node has a linear transfer function. This structure of Neural Network controller is the result of repeated trials (Fig. 1).

At a very basic level, the role of the A/F controller is to supply fuel to the engine such that it matches the amount of air pumped into the engine via the throttle and idle speed by pass valve. This is accomplished with an electronic feedback control system that utilizes a heated exhaust gas oxygen sensor whose role is to indicate whether the engine-outexhaust is rich (i.e., too much fuel) or lean (too much air) (Rumelhart *et al*., 1986) (Fig. 2).

Depending on the measured state of the exhaust gases as well as engine operating conditions such as engine speed and load, the A/F control is changed so as to drive the system toward stoichiometry. Since, the HEGO sensor is largely considered to be a binary sensor (i.e., it produces high/low voltage levels for rich/lean operations, respectively) and since there are time-varying transport delays, the closed-loop A/F control strategy often takes the form of a jump/ramp strategy which effectively causes the HEGO output to oscillate between the two voltage levels (Singhal and Wu, 1989). Researchers have demonstrated that an open-loop recurrent neural network controller can be trained to provide a correction signal to the closed-loop A/F control in the face of transient conditions (i.e., dynamic changes in engine speed and load), thereby eliminating large deviations from stoichiometry (Feldkamp and Puskorius, 1994b). This is accomplished by using an auxiliary Universal EGO (UEGO) sensor which provides a continuous measure of A/F ratio (as opposed to the rich/lean indication provided by the HEGO) during the in-vehicle training process. Deviations of measured A/F ratio from stoichiometric A/F ratio provide the error signal for the EKF training process however, the measured A/F ratio is not used as an input and since the A/F control does not have a major effect on engine operating conditions when operated near stoichiometry then this can be viewed as a problem of training an open-loop controller (Puskorius and Feldkamp, 1991). Nevertheless, researchers use recurrent network controllers to provide the capability of representing the condition-dependent dynamics associated with the operation of the engine system under A/F control and must take care to properly compute derivatives.

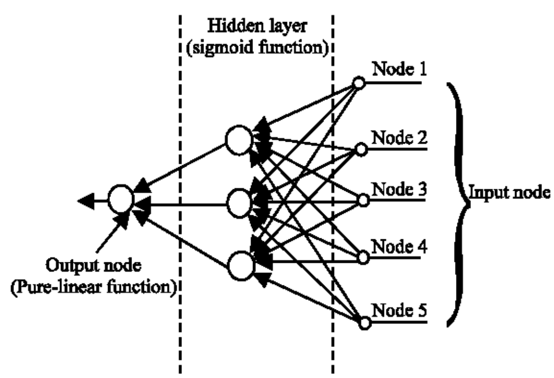

Fig. 1: Structure of neural network controller (5-3-1)

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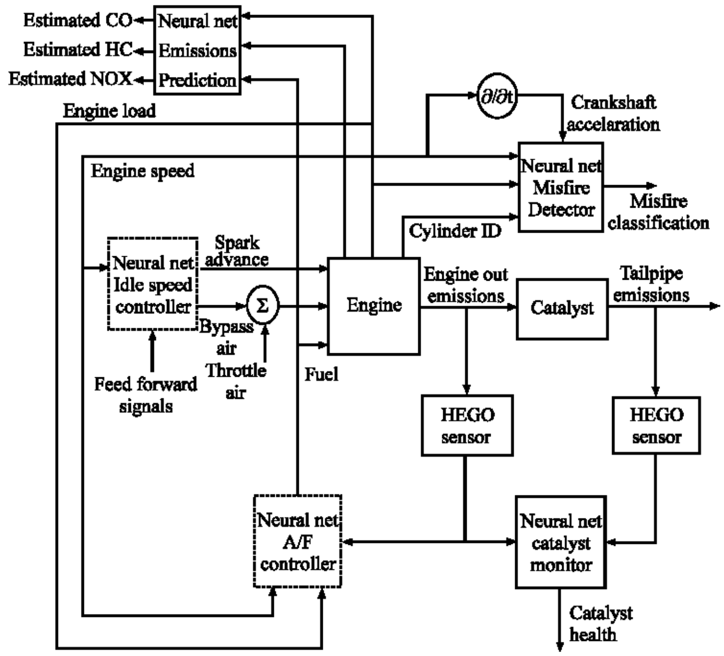

Fig. 2: Neural network representation for automatic engine control

TRAINING THE NEURAL NETWORK CONTROLLER

Increasing levels of pollutants in the atmosphere observed despite the imposition of stricter emission standards and technological improvements in emissions control systems have led to models being developed to predict emissions inventories (Puskorius and Feldkamp, 1993). These are typically based on the emissions levels that are mandated by the government for a particular driving schedule and a given model year. It has been found that the emissions inventories based on these mandated levels do not accurately reflect those that are actually found to exist. That is actual emission rates depend heavily upon driving patterns (Puskorius *et al*., 1996) and real-world driving patterns are not comprehensively represented by the mandated driving schedules.

To better assess the emissions that occur in practice and to predict emissions inventories, experiments have been conducted using instrumented vehicles that are driven in actual traffic (Williams and Zipser, 1989). Unfortunately, such vehicles are costly and are difficult to operate and maintain. The recurrent neural networks can be trained to estimate instantaneous engine-out emissions from a small number of easily measured engine variables (Puskorius and Feldkamp, 1994). Under the assumption of a properly operating fuel control system and catalytic converter, this leads to estimates of tail pipe emissions as well. This capability then allows one to estimate the sensitivity of emissions to driving style (e.g., aggressive versus conservative). Once trained, the network requires only information already available to the power train processor (Werbos, 1990). Because of engine dynamics, the use of recurrent networks trained by KF Methods to enable accurate estimation of instantaneous emissions levels (Puskorius and Feldkamp, 1997) (Fig. 3).

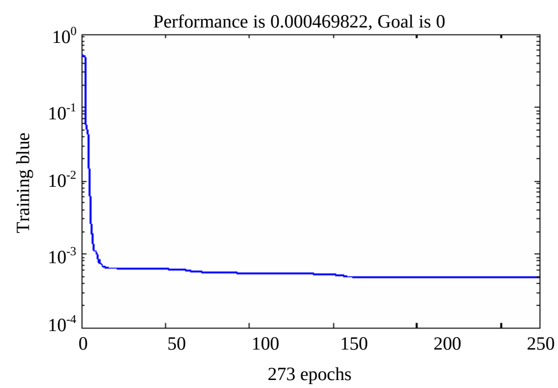

Fig. 3: Graph showing the accurate estimation of emission levels during the training of NN

SIMULATION RESULTS

Researchers have simulated the proposed NN controller using MATLAB which has accurate models of switching components and diodes. The weights and

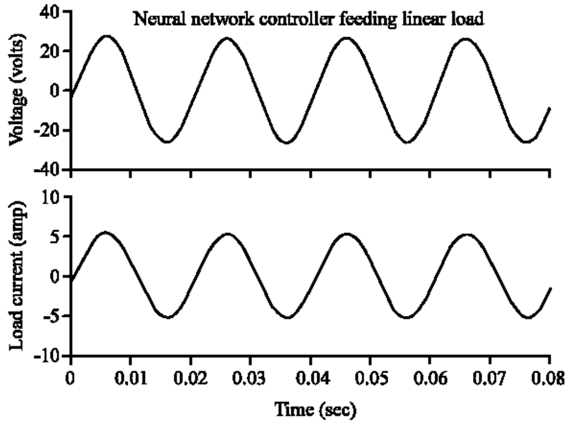

Fig. 4: Neural network voltage and current waveforms for resistive load

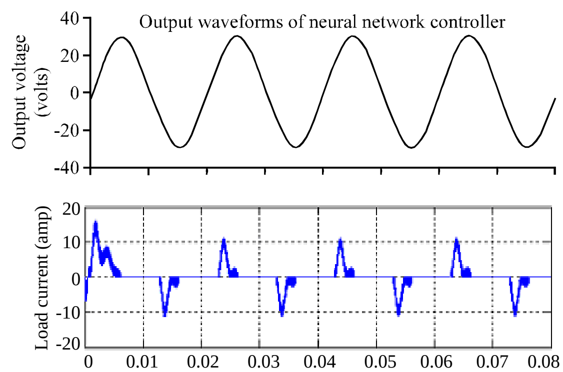

Fig. 5: Neural network voltage and current waveforms for non-linear load

biases from MATLAB simulations are put into the Simulink Model. The steady-state and transient responses of the proposed NN Controlled Method is investigated (Feldkamp and Puskorius, 1994a, b) (Fig. 4 and 5).

SUMMARY OF SIMULATION RESULTS

Decoupling should be used when computation is a concern (e.g., for on-line applications). Node and layer decoupling are the two most appropriate choices. Otherwise, researchers recommend the use of global KF, regardless of network architecture as it should be expected to find better solutions than any of the decoupled versions because of the use of full second-order information.

Effectively, two parameter values need to be chosen for training of networks with KF Methods. The approximate error covariance matrices are always initialized with diagonal value of 100 and 1,000 for weights corresponding to nonlinear and linear nodes, respectively. Then, the user of these methods must set values for the learning rate and process-noise term according to characteristics of the training problem.

Training of recurrent networks, either as supervised training tasks or for controller training can often be improved by multistreaming. The choice of the number of streams is dictated by problem characteristics.

Matrix inversions can be avoided by use of sequential KF update procedures. In the case of decoupling, the order in which outputs are processed can affect training performance in detail. That outputs be processed in random order when these methods are used.

Square-root filtering can be employed to insure computational stability for the error covariance update equation. However, the use of square-root filtering with artificial process noise for covariance updates results in a substantial increase in computational complexity. The nonzero artificial process noise benefits training, by providing a mechanism to escape poor local minima and a mechanism that maintains stable covariance updates when using the Riccati update equation.

The KF procedures can be modified to allow for alternative cost functions (e.g., entropic cost functions) and for weight constraints to be imposed during training which thereby allow networks to be deployed in fixed-point arithmetic.

CONCLUSION

A simulation study of the conventional and neural based controller was done. The Analogue Neural Network controller is designed and its performance has been validated using PSPICE. Based on the results, the following conclusions can be made.

The KF procedures derived on the basis of a first-order linearization of the nonlinear system this may provide a limitation in the form of large errors in the weight estimates and covariance matrix, since the second-order information is effectively developed by taking outer products of the gradients.

The KF is used to provide a more accurate means of developing the required second-order information without increasing the computational complexity.

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