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Modeling of 12-Cylinder Camless Engine with Neural Networks

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***Abstract*— The 12-cyliner camless engine breathing process will be modeled with artificial neural networks (ANN's). The inputs to the net are the intake valve lift (IVL) and intake valve closing timing (IVC) whereas the output of the net is the cylinder air charge (CAC). In camless engine a control system should be designed to track desired cylinder air charge as demanded by the driver and thus satisfy torque requirement. For efficient engine performance the pumping loss (PL) must be minimized while tracking the cylinder air charge. Towards this end, the pumping loss as a function of the intake valve lift and intake valve closing timing is modeled with the aid of the neural networks. The developed neural net model predicts the cylinder air charge and pumping loss well and can be used for camless engine control design.**

***Keywords*— 12-cylinder camless engine, artificial neural networks, modeling**

I. Introduction

One of the major challenges in the camless IC engine design is controlling the cylinder air charge (CAC) rapidly and accurately based on conventional measurements. A feedback control system that is responsible for this task has been developed by [1]. It consists of a feedforward controller, a CAC estimator and an on-line parameter estimator which is used to adapt the feedforward controller parameters using the CAC estimate. It has been shown in [2] that the feedforward controller can be modeled by inverting the camless engine breathing process ANN model where the results for a 4-cylinder camless engine were presented. Furthermore, ANN modeling and control of the 8-cylinder camless engine breathing process was performed in [3].

In this research, we will model the more challenging 12-cyliner camless engine breathing process with artificial neural networks (ANN's). The inputs to the net are the IVL and IVC whereas the output of the net is the CAC. Another important output that will be taken into account in neural net modeling is the pumping loss (PL) which is usually minimized in camless engine control applications. The ANN is trained with engine input output data at a constant speed of 1500 rpm. The ANN model forecasts the CAC and the pumping loss at this speed.

Artificial neural networks (ANN's) have received a lot of attention in recent years due to their attractive capabilities in forecasting, modelling of complex nonlinear systems and control. Applications of neural networks include many various fields among which are engineering and business. ANN's have been used for forecasting load [4,5], gasoline consumption [6], energy [7], space weather [8], outdoor sound transmission [9], streamflow [10], wind waves [11] and financial indicators [12-14]. Examples of industrial processes for which modelling and control using neural networks have been investigated include internal combustion engines [2,15], two-stage combustor burning ethylene in air [16], hot-wire temperature sensor [17,18] and steel making process [19].

Artificial neural networks are widely used for forecasting. A large number of successful applications have shown that neural networks can be a very useful tool for time series modelling and forecasting [20,21]. In addition, the simulation experiments of [22] show that neural networks are valuable tools for forecasting nonlinear time series when compared to other traditional linear methods. Even though it may sound that ANN's are not needed for modelling and forecasting linear time series due to the well developed linear system theory, they are competent in this [23]. Numerous articles comparing performances of statistical and neural networks models are available in the literature [24]. The ANN model is trained with historical time series input-output process data or observations and is then used to predict the output in the future.

II. Neural Networks

Artificial neural networks were originally inspired as being models of human nervous system. They have been shown to exhibit many abilities, such as learning, generalization, and abstraction [25]. Useful information and theory about ANN's can be found in [26]. These networks are used as models for processes that have input-output data available. The input-output data allows the neural network to be trained such that the error between the real output and the estimated (neural net) output is minimized. The model is then used for different purposes among which are estimation and control.

The neural net structure to be used for modeling the camless engine breathing process is shown in Figure 1. The inputs are the intake valve lift (IVL) and intake valve closing timing (IVC) whereas the outputs are the important variables for control design, namely, the cylinder air charge (CAC) and pumping loss (PL). CAC needs to be tracked based on the driver's torque demand while minimizing the pumping loss. IVL and IVC feed forward through a hidden layer to the CAC and PL. The hidden layer contains

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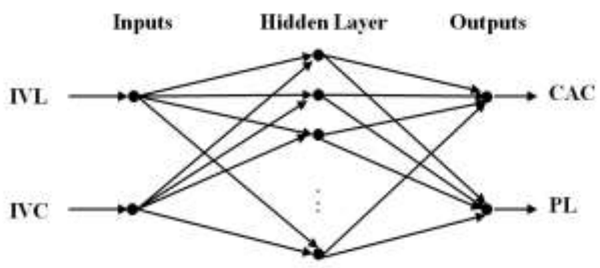

Figure 1. Camless engine neural net structure

processing units called nodes or neurons. Each neuron is described by a nonlinear sigmoid function. The inputs are linked to the hidden layer which is in turn linked to the outputs. Each interconnection is associated with a multiplicative parameter called weight. Note that the feed-forward neural net of Figure 1 has only one hidden layer and this is the case that we are going to consider. A number of results have been published showing that a feed-forward network with only a single hidden layer can well approximate a continuous function [27,28]. In practice, most of the physical processes such as the camless engine are continuous. However, the results of this paper can easily be extended to include multi layer neural networks.

An artificial neural net mathematical model that represents the structure shown in Figure 1 is written as

$$Y = f(U) = W_o * \tanh(W_i * U + B_i) + B_o \qquad (1)$$

where, Y is a column vector which contains the 2 outputs of the process, U is a column vector that contains the 2 inputs of the process, W_o is a matrix of size 2xn that contains the weights of the neural net model from the hidden layer to the outputs with n being the number of neurons in the hidden layer, W_i is a matrix of size nx2 that contains the weights of the neural net model from the inputs to the hidden layer, B_i (not shown in Figure 1) is a column vector of size n that contains the biases from the inputs to the hidden layer and B_o (not shown in Figure 1) is a column vector of size 2 which contains the biases from the hidden layer to the outputs.

The weights and biases of the ANN are determined by training with the historical input-output data. Backpropagation is an example of a training algorithm. The available data is divided into two parts: one part is used for training the net whereas the other usually smaller part is used to test the performance of the ANN. The number of hidden neurons n affects the performance of the neural net over the training and test sets of data. More neurons make the fitting of data more accurate over the training region. It is more important to check the generalization performance of the model over the test set of data since it was not used to calculate the parameters of the model. The number of nodes is usually chosen by trying different values and selecting the one that gives best results over both the training and test regions. The neural net modeling of the 4-cylinder and 8-cylinder camless engine breathing processes was performed in [2] and [3], respectively. Similar ideas are used in this research to model the 12-cylinder engine breathing process with neural networks.

III. The 12-Cylinder Camless Engine Model

The 12-cylinder camless engine operation has to be based on controller design that regulates the cylinder air charge (desired torque as determined by the diver) and minimizes the pumping losses by adjusting the intake valve lift and closing timing. The engine torque is set by the amount of air that enters the cylinder during the intake (breathing) stroke. The intake valve motion is the main factor that specifies the cylinder air charge (CAC) and pumping loss (PL). Thus, it is essential to regulate the intake valve lift (IVL) and closing timing (IVC) to achieve the best engine performance. The intake valve opening timing (IVO) will be set at the top dead center or zero degrees of crank angle. It has been shown in [29] that setting the IVO equal to zero degrees of crank angle does not influence the camless engine performance. An important remark to point out here is that the camless engine pumping loss is much less than the conventional engine pumping loss. This is due to the fact that the camless engine does not have a throttle.

During breathing air enters into the engine cylinders while the intake valve is open. The mass of air that enters the cylinder during the breathing process is called cylinder air charge (CAC). This quantity depends on IVL, IVC and engine speed (S). We will consider IVL and IVC as inputs whereas the engine speed S will be considered as a system parameter. The outputs are CAC and PL. A model based on thermodynamics laws was developed for the breathing process in [29]. The cylinder air charge and pumping loss one time unit ahead are written as

$$\mathrm{CAC}(t+1) = f(\mathrm{IVL}(t), \mathrm{IVC}(t), \mathrm{S}(t)) \qquad (2)$$

and

$$\mathrm{PL}(t+1) = g(\mathrm{IVL}(t), \mathrm{IVC}(t), S(t)) \qquad (3)$$

where, f and g are nonlinear functions. Based on this model input-output data have been generated at a speed S = 1500 RPM and are represented graphically as shown in Figure 2. The data contains 112 patterns. Each pattern includes data about the two inputs and the corresponding two outputs. The intake valve lift ranges from 0.5 to 8 mm with a 0.5 mm increment, whereas the intake valve closing timing ranges from 60 to 180 degrees with a 20 degree increment of crank angle. Ninety six of the one hundred twelve data patterns are used to train an artificial neural net model for the breathing process, whereas the remaining sixteen data patterns are used to test the performance of the model. The training was done with the software package Matlab. We ran experiments for different numbers of hidden neurons. It was observed that the quality of the results depends on the number of hidden neurons. The results are summarized in Table 1. We choose the neural net with eight hidden neurons since it is the minimum number of neurons with lowest training and test errors for both CAC and PL. Note that for hidden neurons larger than 8 the training error keeps dropping but the test error goes up due to over fitting which is not desirable in neural net modeling. The real and predicted (ANN) values of cylinder air charge are plotted in Figure 3 as a function of the index. Similarly, the real and predicted (ANN) values of pumping loss are plotted in

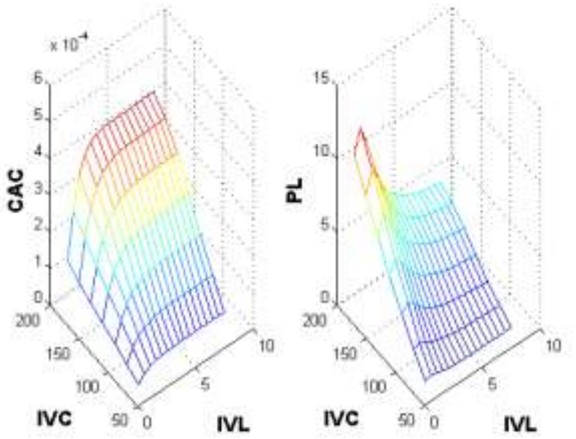

Figure 2. CAC and PL surfaces for the 12-cylinder camless engine

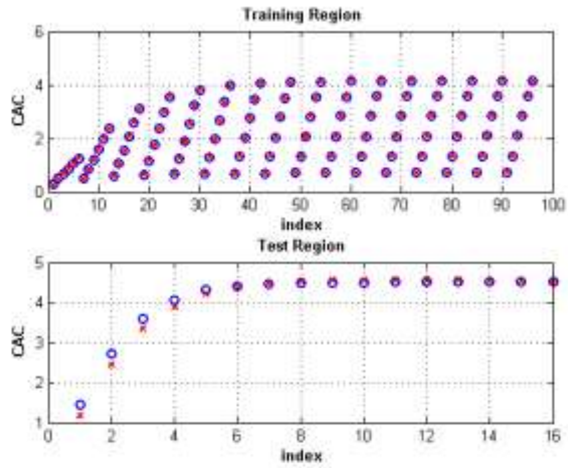

Figure 3. ANN modeling results for CAC of the 12-cylinder camless engine

Figure 4 as a function of the index. Note that the predicted values are very close to the real ones. Therefore, the developed neural net model is accurate.

IV. Conclusions

A control oriented artificial neural net model was developed for the breathing process of the 12-cyliner camless engine. The model predicts the cylinder air charge and pumping losses as functions of the intake valve lift and closing timing well and thus represents an excellent model of the 12-cylinder camless engine. The developed model can be used in the future for controller design which is vital for the 12-cylinder camless engine operation.

TABLE I. Neural net modelling errors for different numbers of neurons *n*

n	CAC training least square error	PL training least square error	CAC test least square error	PL test least square error
1	0.6777	0.3672	1.5372	4.0988
2	0.0450	0.1056	0.4203	0.6767
3	0.0282	0.0877	0.3109	0.3926
4	0.0050	0.0112	0.1122	0.3038
5	0.0012	0.0016	0.2768	0.3557
6	0.0018	0.0023	0.0409	0.1554
7	0.0010	0.0005	0.0140	0.0492
8	**0.0001**	**0.0003**	**0.0167**	**0.0195**
9	0.0012	0.0012	0.0848	0.1631
10	0.0000	0.0001	0.0053	0.0563
11	0.0000	0.0001	0.0198	3.6036
12	0.0000	0.0001	2.0790	6.3887

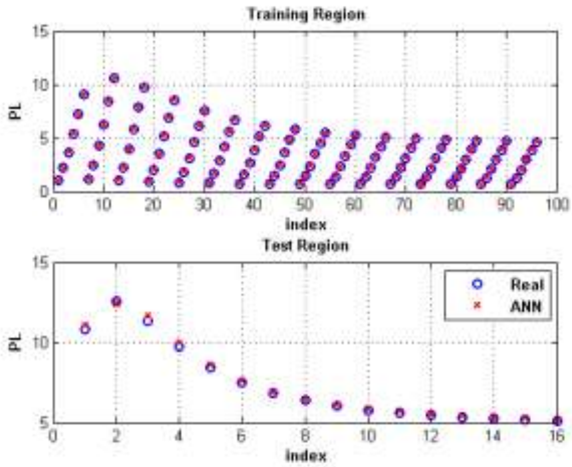

Figure 4. ANN modeling results for PL of the 12-cylinder camless engine

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Moh’d Sami Ashhab earned his M.S. and Ph.D. degrees in mechanical engineering / control and dynamics from The University of California, Santa Barbara, U.S.A. in 1996 and 1998, respectively. After working for about four years in industry in the U.S.A., he joined the Hashemite University in Jordan in year 2002 where he is now a mechanical engineering Professor. He is currently spending his sabbatical leave at the mechanical engineering department, American University of Ras Al Khaimah, UAE. His primary interests are in the areas of control, dynamics, automation, MEMS and NEMS, artificial intelligence, optimization, simulation, energy and industrial applications.