Artificial Neural Networks based Methodologies for Optimization of Engine Operations

Anant Bhaskar Garg, Parag Diwan, Mukesh Saxena

Abstract— This paper presents overview of applications of artificial neural networks (ANN) in the field of engine development. Various approaches using ANN are highlighted that resulted in better modeling of engine operations. Using ANN we can reduce engine development time. The paper discusses ANN approach, algorithms and importance of architecture. This will also help in advancing ANN research.

Index Terms—Artificial Neural Networks, Architecture, Activation Functions, Alternative Fuels, Engine Parameters, Optimization of Operations, Training, and Modeling

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1. Introduction

IN order to comply with increasingly stringent emission standards and meet drivability requirements, modern automobile engines are equipped with an increasing number of subsystems and controlling elements. This has resulted in increased instrumentation that requires calibration with respect to best operating conditions. Engine Management Systems (EMS) refers to the collective unit comprising of sensors, actuators, signal conditioners, power-amplifiers and a microprocessor. The system performs functions of real-time engine control and diagnostics and termed as Electronic Control Unit (ECU). EMS is designed to enhance fuel economy, reduce emissions and improve overall drivability over the range of operating conditions of interest.

Conventional calibration methods rely on dynamometer mapping and transient vehicle testing to arrive at a vehicle calibration. However, as vehicle complexity is increased, the calibration process, its duration, and its cost grow. Even for relatively simple systems, achievement of optimized calibrations may become impracticable to accomplish [1]. Vehicle performance depends on the vehicle and driveline specifications, as well as engine variables such as torque, fuel consumption, and emission maps, and ECU's variables such as engine speed and throttle angle [2]. Thus for obtaining engine fuel consumption and emission in terms of calibration parameters, an engine model is required. Because of highly complex and nonlinear nature of internal combustion engines, building analytical models is difficult and one usually reverts to black box type empirical modeling [1], [3], [4], [5].

A very powerful method among black-box modeling techniques is the artificial neural network modeling which has been widely used in various branches of engineering in recent years [6], [7], [8], [9]. This technique aims to significantly decrease dynamometer test requirements by generating mathematical models of the engine outputs using a smaller subset of dynamometer tests. Once the mathematical models have been developed, the calibration maps can be optimized using techniques such as gradient procedures [3]. The objective of this work is to reduce calibration effort while realizing the potential benefit from advanced engine technology. Neural-networks have been trained to perform complex functions in various fields of application, including pattern recognition, identification, classification, speech, vision, and control systems. Today neural-networks can be trained to solve problems that are difficult for conventional computers or human beings to solve. Neural-networks are composed of simple elements connected in series-parallel arrangements. These elements are inspired by biological neurons in the nervous system of the human beings as shown in Figure 1.

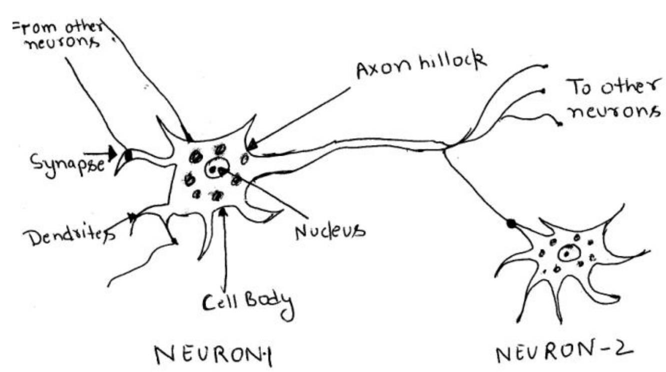
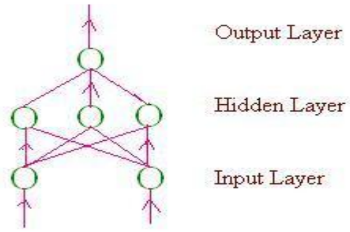


Fig. 1: Basic Model of Biological Neuron

As in nature, the network function is determined largely by the connections between elements. A neural-network can be trained to perform a particular function by adjusting the values of the connections called weights between the adjacent elements as shown in three layers Figure 2. The basic processing element of a neural-network is a neuron. Fundamentally, a biological neuron receives inputs from certain sources, combines them in some way, and performs a generally non-linear operation on the results, and presents them as the output. Neural-networks operate like a 'black box' model; the user does not need to know any detailed information about the system.

Fig. 2: Artificial Neural Network model with input, hidden, and output layers



2. Artificial Neural Networks in Engine Development

Based on applications of artificial neural networks we can classify them for management of engine operations, alternative fuels, and architecture optimization of neural networks.

2.1. Management of Engine Operating Parameters

Aries et. al. [10] described on the experimental identification and validation of recurrent neural network models for air-fuel ratio estimation and control in spark-ignited engines. Akcayoli et. al. [11] used DI diesel engine and ANN for predicting torque, power, SFC, soot formation with speed and injection pressure as inputs. Gisca et. al. [12] described a method for determining the functioning parameters of the internal combustion engine, such as pressure in cylinders or the air-fuel ratio. Isermann and Muller [13] described advanced engine control systems require accurate models of the thermodynamic-mechanical process, which are substantially nonlinear and often time-variant. A new training algorithm for online adaptation of look-up table is introduced which reduces the convergence time considerably. Lawrynczuk [14] studied nonlinear Model-based Predictive Control algorithms for MIMO processes modeled by means of neural networks of a feed forward structure.

Samadani et. al. [15] described the problem of optimization of diesel engine performance and emission. The optimization goal is to minimize NOx and soot while maximizes engine performance. A neural network model of the engine, which has proved to be an efficient tool for simulating diesel engine combustion, was developed. Stobart and Deng [16] used a parallel neural network structure to predict the smoke output of a diesel engine based on NLARX models. Sekmen et. al. [17] studied artificial neural-networks (ANNs) are used to determine the effects of injection pressure on smoke emissions and engine performance in a diesel engine. Experimental studies were used to obtain training and test data. Injection pressure and engine speed have been used as the input layer; smoke emission, engine torque and specific fuel consumption have been used as the output layer. Two different training algorithms were studied. They described two back-propagation learning algorithms are used to predict of the torque, power, specific fuel consumption, and smoke emission of diesel engine using different injection pressure and engine speed. Injection pressure and engine speed have been used as the input layer; engine torque, specific fuel consumption, and smoke emission have also been used as the output layer. The performance of these models is evaluated and the results compared with experimental values. The LM algorithm with 11 neurons has produced the best results and for the torque the mean absolute percentage errors are limited to about 7-9% both algorithms. For also the specific fuel consumption the mean absolute percentage errors are limited to 6-8.8% both algorithms. The smoke emission predicted using neural network is not considered within the acceptable range. With these results, it is believed that the ANN can be used for prediction of torque and specific fuel consumption as an appropriate method in diesel engine.

Thompson et. al. [18] studied neural network-based engine modeling offers the potential for a multidimensional, adaptive, learning control system which does not require knowledge of the governing equations for engine performance or the combustion kinetics of emissions formation that a conventional map-based engine model require. Tutuncu and Allahverdi [19] described the ANN might play an important role in modeling and prediction of the performance and emission characteristics of combustion process. They said the potential of ANN as a design tool in many areas of combustion engineering. Walters et. al. [20] described an evaluation of a neural network technique for modeling fuel spray penetration in the cylinder of a diesel internal combustion engine. The model was implemented using a multi-layer perceptron neural network. Two engine-operating parameters were used as inputs to the model, namely injection pressure and in-cylinder pressure. Spray penetration lengths were modeled on the basis of these two inputs. The model was validated using test data that had not been used during training, and it was shown that semi automated classification of complex diesel spray data is possible.

Wenyong [21] described algorithm-using ANN for DI diesel engine for various control strategy for managing engine dynamics. Wu et. al. [22] et al used Artificial Neural Networks (ANN) to model the airflow rate through a 2.4 liter VVT engine with independent intake and exhaust camshaft phasers. The procedure for selecting the network architecture and size is combined with the appropriate training methodology to maximize accuracy and prevent over fitting. After completing the ANN training based on a large set of dynamometer test data, the multi-layer feed forward network demonstrates the ability to represent airflow rate accurately over a wide range of operating conditions. The ANN model is implemented in a vehicle with the same 2.4 L engine using a Rapid Prototype Controller. Comparison between a mass airflow (MAF) sensor and the ANN model during a typical dynamic maneuver shows a very good agreement and superior behavior of the network during the transient. Practical recommendations regarding the production implementation of the ANN are provided as well the Air Flow Rate through a 2.4 Liter VVT Engine. Wu et. al. [23] proposes an optimization framework and a simulation-based approach for calibrating high-degree of-freedom engines. The high-fidelity simulation tool is developed first as a virtual engine, capable of modeling the relationship between independent variable set points and engine performance. After identifying model coefficients with a li-

ISSN 2229-5518

mited set of experimental measurements, the tool can be used to create any desired set of data and simulate new designs not yet available in hardware. However, the prospect of executing the simulation hundreds of times within the optimization framework imposes a need for much faster and yet accurate surrogate models.

The artificial neural networks (ANN) are used to create such computationally efficient models. The ANNs are trained on operating points chosen by a design-of–experiments technique and produced by high-fidelity simulations. The computational speed of neural networks allows solving optimization problems with various formulations of optimization objectives and constraints. This study demonstrates the use of the proposed algorithm for maximizing the WOT torque of the prototype VVT engine with dual-independent cam-phasers. Zweiri, [6] used Artificial Neural Network to estimate the indicated torque of a single- cylinder diesel engine from crank shaft angular position and velocity measurements and found that ANN based estimator was significantly fast. Hafner et. al. [24] described the different applications, where neural networks are utilized for modeling and control of diesel combustion engines. The presented engine optimization tool represents a further example of how neural net models can successfully be used in the automotive section.

2.2. Applications with Alternative Fuels

Gholamhassan et. al. [25] performed combustion analysis to evaluate performance of a commercial DI engine using vegetable cooking oil as an alternative fuel. They used ANN for nonlinear mapping between input and output parameters. They observed that the ANN model can predict the engine performance and exhaust emissions quite well with correlation coefficient (R) were 0.9487,0.999, 0.929 and 0.999 for the engine torque, SFC, CO and HC emissions, respectively. Obodeh and Ajuwa [26] evaluate the capabilities of ANN as a predictive tool for multi-cylinder diesel engine NOx emissions. The experiments were carried out with a stationary light-duty Nissan diesel engine test-rig designed and assembled to allow testing of the engine in a laboratory environment. Standard laboratory procedure was used to measure the engine operating parameters and its tailpipe emission. ANN were trained on experimental data and used in predicting diesel engine NOx emissions. ANN modeling has proved to be an excellent tool to predict NOx emissions for diesel engine. Malaczynski et. al. [27] discussed the practicality of implementing an ANN based algorithm performing real time calculation of the volumetric efficiency for an engine with variable valve actuation.

Ghobadian et. al. [28] studied ANN modeling on diesel engine using waste cooking biodiesel fuel to predict the brake power, torque, and specific fuel consumption and exhaust emissions of engine. They found the ANN provided accuracy and simplicity in the analysis of the engine performance. Manjunatha et. al. [29] used ANN to predict the emission characteristics of a biodiesel and its blends operated at different load condition on a single cylinder diesel engine. ANN was developed based on the available experimental data. Multi layer perceptron neural network was used for nonlinear mapping between inputs and outputs parameters of ANN.

Prasad and Mohan [30] studied the experimental investigations carried out on direct injection (DI) and indirect injection (IDI) type engines at recommended injection pressure of respective engines with methyl esters of jatropha oil. As per Prasad [31] ANNs do not need an explicit formulation of physical relationships for the concerned problem. In other words, they only need examples of the subject in the relevant context and show the possibility of using the neural networks for predictions of engine exhaust emissions from, a diesel engine. They used biodiesel with different blends and operated at different load. Shivakumar et. al. [32] observed CI constant speed diesel engine with vegetable oils as biodiesels and measures performance and emission characteristics using ANN and showed analysis on various parameters.

3. Neural Network Algorithms and Approaches

Application of neural networks to engine operation data has attained increasing importance mainly due to the efficiency of present day computers on one hand and stringent emission norms for engine on the other hand. The ability of Artificial Neural Network as a system identification tool is used to model non-linear behavior of engine operations. We will perform detailed study using different algorithms and choose the one that provides the best results for given set of data of engine parameters. Initially an approach based on the input – output relation among input vector parameters and output parameter is used to train the neural network as per different learning algorithms available for training of neural network. Various toolbox functions such as different types of feed-forward neural network, training functions, activation function, learning functions, initialization function and performance functions available will be tested and the most suitable combination will be selected.

The ability of ANN to understand and properly classify a problem of highly non-linear relationship has been established and the significant consideration is that once trained effectively ANN can classify new data much faster than it would be possible with analytical model. A neural network is a massively parallel-distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects [33]:

1. Knowledge is acquired by the network through a learning process.
2. Inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

Simply it works on the input-output mechanism. Neural networks can also be defined as parameterized computational non-linear algorithms for data/signal/image processing. These algorithms are either implemented on a general –purpose computer or are built into a dedicated hardware. An artificial neuron network is characterized by:

1. Architecture
2. Training or learning (determining weights on the connections)
3. Activation function

A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Network is adjusted in terms of weight and architecture, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network.

The main objective of learning algorithm is to provide a methodology to teach the network for a given task (to optimize the cost function). There are numerous algorithms available for training neural network models and most of them can be viewed as a straightforward application of optimization theory and statistical estimation [34]. These algorithms generally use gradient descent form. This is done by simply taking the derivative of the cost function with respect to the network parameters and then changing those parameters in a gradient-related direction. Some of the algorithms are Gradient Descent Algorithm, and Levenberg-Marquardt Algorithm. Some types of networks are feed-forward network, Radial Basis Function network which are used in above investigations [35].

4. Conclusion

ANNs are suited for formulating objective functions, evaluating the specified engine performance indices with respect to the controllable engine variables and thus deriving the engine calibration correlations. They are computationally efficient for optimization requiring hundreds of function evaluations. Neural network requires better understanding of system dynamics or data capture for better results. Neural networks architectures, combinations of networks, and different algorithms play an important role on the performance. Real-time operation and mapping of complex, non-linear and dynamic patterns in engine operations are challenges to be met in today's engine development. There is a need to use ANN as a performance critical tool that saves cost and time in developing new models and methodologies for overall engine management. Further it will help in accessing which algorithm is best suitable for a particular situation.

Acknowledgments

First author is grateful to Dr. S. J. Chopra, Chancellor,
Dr. Parag Diwan, Vice Chancellor, Dr. Shrihari, Dean, and Dr. Mukesh Saxena, UPES for giving opportunity to conduct this research, guidance, and directions from them time-to-time. And help from colleagues especially Narayan Khatri and P. S. Ranjit in understanding engine operations and others from CIT.

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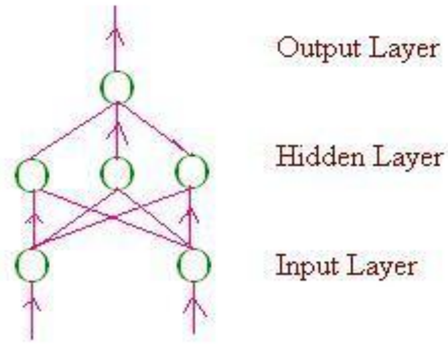

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