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신경회로망을 이용한 디젤기관의 동정과 속도제어에 관한 연구

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A Study on the Identification and Speed Control of Diesel Engines Using Neural Networks

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Key words : 신경회로망디지털조속기(Neural Digital Governor), 하이브리드제어기(Hybrid controller), 뉴럴에뮬레이터(Neural Emulator)

Abstract

디젤기관은 실린더 내경의 크기, 실린더수 및 회전수에 따라 착화지연, 연소지연 및 디젤기관의 각종 정수가 달라지므로 비선형이 심한 시스템이다. 본 연구에서는 신경회로망을 이용하여 발전기를 구동하는 디젤기관의 속도를 제어하는 디젤기관 신경회로망 디지털조속기를 제안한다. 이를 위하여 3상 50kW 발전기를 구동하는 4행정 4실린더, 1800 rpm ISUTSU 디젤기관의 실제 운전데이터로부터 뉴럴에뮬레이터를 구한다. 최적의 뉴럴에뮬레이터 구성을 위하여 다양한 역전파알고리즘으로 학습을 행하고 결과를 비교한다. 또한 디젤기관의 역으로부터 뉴럴 제어기를 구성하고 뉴럴에뮬레이터로 시뮬레이션을 행한다. 외란이 존재하는 경우에도 효과적인 뉴럴제어기를 구성하기 위하여 선택적 뉴럴제어기의 사용을 제안한다. 또한 응답성을 향상하고 정확한 목표치추종을 위하여 PI제어기를 보조제어기로 사용하는 하이브리드제어기를 구성하여 시뮬레이션을 통하여 성능이 향상됨을 보인다.

1. Introduction

Diesel engine is highly non linear system because various kinds of parameters change according to size and number of cylinder and revolution per minute(rpm). So, it is difficult to find the appropriate parameters controlling the diesel engine system satisfactory over all situations[1]. Because of these difficulties of controlling diesel engine, intelligent control using fuzzy and neural networks tendency to be applied to real plant.

Meanwhile, according to increasing reliability of microprocessor and electronic system, hydro-mechanical speed controller of diesel engine is being replaced by electric or digital controller. So,

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it is easy to apply intelligent control algorithm to these diesel engines. This paper proposes one available method to control speed of diesel engine using neural networks. Firstly, neural emulator is composed with real data acquisited from 4 cycle 4 cylinder, 1800rpm diesel engine driving 50kW electric generator. Then neural controller is proposed from inverse of neural emulator after ascertaining performance of neural emulator by validate data and test data different from training data among real data set. It is difficult to train neural networks effectively to cover overall cases due to difficulty to acquisite data of all available real cases. Due to these reasons neural emulator does not work exactly like real diesel engine and neural controller also. So this paper propose hybrid controller which is composed with neural controller and conventional PI controller, and try to show that this hybrid controller can be used to control speed of diesel engine through the simulation.

2. Design of Neural Emulator for diesel engine

2.1 Modelling of Diesel Engine

There are many models of diesel engine according to size and speed by authors of various papers[3,6,7,8,9-12]. But in this paper, combustion and revolution systems are modelled as a first-order system respectively as shown in Fig. 1[13] because characteristic of actuator and combustion systems have much influence on the behaviour of diesel engine. Where, L is the total dead time summing injection delay and combustion delay, T_c and k_c are time constant and steady state gain respectively in combustion system of engine, T_a and k_a are those of actuator, K_L is the load characteristics to convert rpm to horse power at operating rpm, J is the moment of inertia including propeller and additional water effects, Kg · m · sec². Yo is the constant to convert horse power developed by engine to rpm.

2.2 Structure of a Neural Emulator

The internal structure of a neural emulator is configured like Fig. 2 based on a diesel engine modelled as third order system[11,12].

The neural emulator architecture considered in this paper is composed of three layers; an input layer, a hidden layer and an output layer.

Based on the third-order system like Fig. 2 engine control signal u(k), engine output rpm y(k) and their delayed signals u(k-1), u(k-2), u(k-3), y(k-1), y(k-2) and y(k-3) are chosen as input of neural emulator. In order to determine the proper number of hidden node in Fig. 2, neural emulator was trained respect to the various number of hidden node. As expected, if the number of hidden node small, the error of

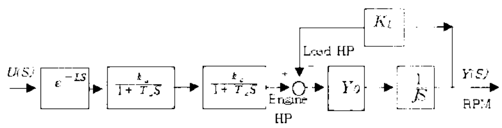

Fig. 1 Block diagram of the controlled system in case of regarding the engine dead time.

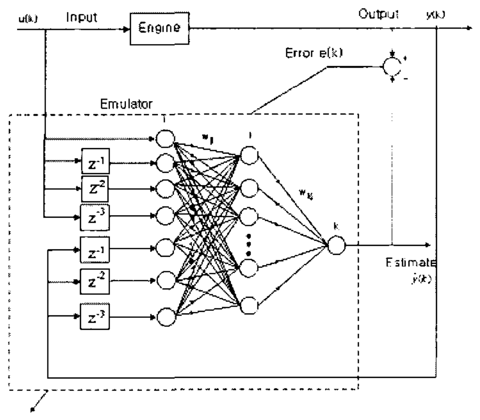

Fig. 2 Internal structure of a neural emulator.

networks tends to be converged at large error. But if the number of hidden node is too large, the convergency tends to be improved, but the number of epoch for training to be large. Based on try-and-error experiment[5], when the node number is selected from 9 to 12, this network meets convergency speed. Finally, eleven nodes for hidden layer are chosen.

The output layer consists of only one node corresponding to the estimate value of the engine output. The tangent sigmoid function is used for the activation function of the input neurons and the hidden neurons and the linear function for output layer[2].

2.3 Data Collection for neural network training

To obtain training data set, the following system as shown in Fig. 3 is considered and then input and output data patterns are collected. Data acquisition is carried out from a diesel engine speed control system composed of four parts; a digital governor, an actuator, a MPU, and a PC. Whenever MPU approaches close to the fly wheel teeth, it generates pulse relating to rpm and this rpm data makes feedback to the digital governor. According to the difference between reference rpm and feedback rpm, appropriate control input is generated. This control input signal makes an actuator be operated and the fuel quantity injected into the

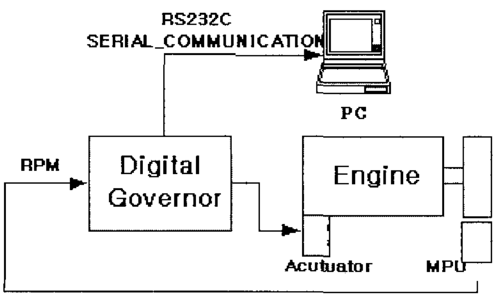

Fig.3 Diesel Engine System used in experiment

engine is adjusted according to the control input. And reference, rpm and control input are transmitted to the PC and stored in the shape of text files using RS232 serial communication.[4]

Diesel engine used in this experiment is 4 cycle 4 cylinder, 1800 rated rpm driving 50kW 3 phase 220V AC generator. Fig. 4 and 5 are dynamic characteristic graphs of control input and output(rpm) when disturbance are added to F.O. rack between 3 and 6 sec and load disturbance between 6 and 9 sec, which is used for training neural networks.

2.4 Training Results with respect to various Backpropagation Algorithms

To train neural network three kinds of backpropagation algorithms are used to compare learning efficiency. Fig. 6 shows the results of

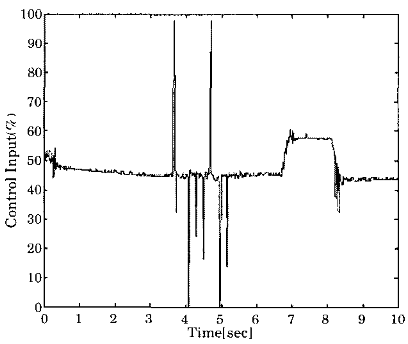

Fig. 4 Control input signal of the diesel engine used for training

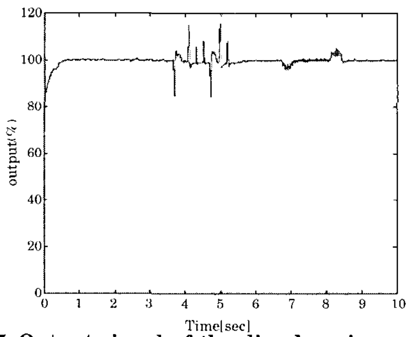

Fig. 5 Output signal of the diesel engine used for training

mean squared error according to backpropagation with momentum(BPM), adaptive backpropagation (BPA) and Levenberg-Marquardt backpropagation (BPLM). In this paper BPLM is used by the result of analysis with responses of neural networks and real diesel engine and convergency speed to the error goal. Fig. 7 shows the dynamic response characteristics of neural networks trained by BPLM algorithm.

In Fig. 7 output of neural networks follows that of real diesel engine satisfactory.

To confirm performances of training the learned neural network are tested by validate data which is acquisited from same diesel engine by another experiments. Fig.8 shows dynamic responses of neural network and real diesel

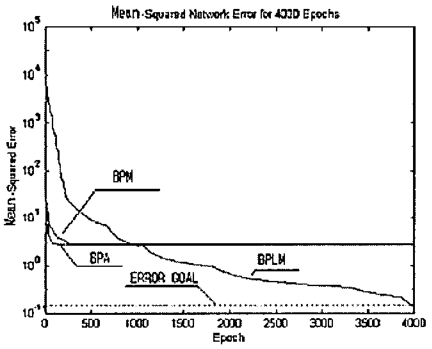

Fig. 6 Mean squared errors by BPM, BPA, BPLM

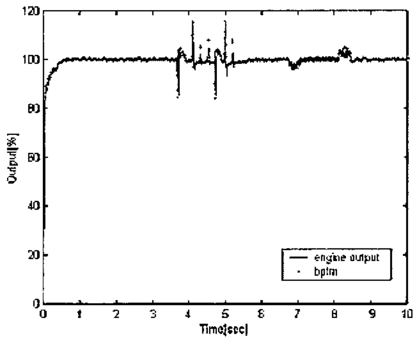

Fig. 7 The dynamic response characteristics of neural networks trained by BPLM algorithm

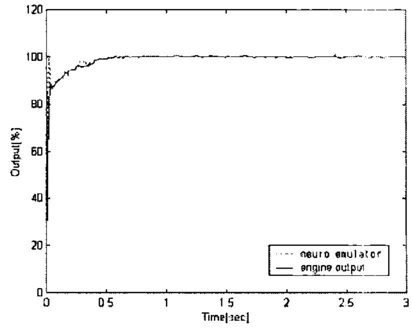

Fig. 8 The dynamic response characteristics of the diesel engine and the neural emulator using validate data

plant. In Fig. 8 neural emulator follows real diesel plant satisfactory.

3. Design of Neural Controller for diesel engine

3.1 Neural Controller Design

For purpose of composing a series control system, a neural network is employed to identify inverse dynamics models through learning. Inverse dynamics identification is regarded as finding the inverse mapping of the plant as illustrated architecture in Fig. 9.

This architecture is similar to the above mentioned plant identification scheme, but the input signals of networks are different from the case of plant modeling. Since this inverse identification is obtained for control purpose, it should generate the control signal u(k) with respect to output signal y(k). The following Fig. 10 shows the comparison with the output of the neural controller trained using BPLM algorithm and the training data control input.

And Fig. 11 is the control input generated by neural controller with validate data and that of real plant. In Fig. 11 there are some error between real data and generated data by neural controller. This is considered now that training

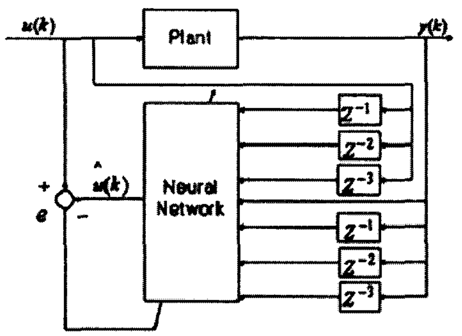

Fig. 9 Identification of plant inverse dynamics.

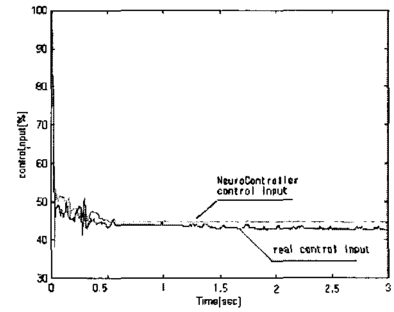

Fig. 11 The dynamic response characteristics of neural controller by using validate data

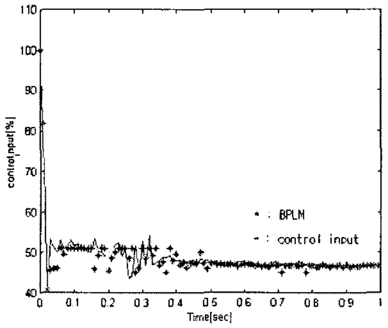

Fig. 10 The dynamic response characteristic of control input generated by the neural controller trained with training data and that of real plant

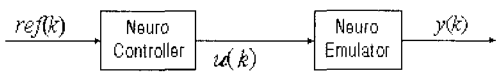

Fig. 12 Series neural control schemeu(k)

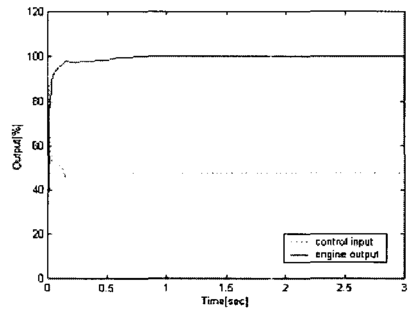

Fig. 13 The dynamic response characteristics of the engine by using series control system

data is not covered all cases and neural controller is not exact inverse of diesel plant. So there are some difficulties to use neural controller for speed control system of diesel engine.

3.2 Design of Neural Control System

The neural control scheme is shown in Fig. 12. In training the neural network, the reference is included in training data because the training

data is collected based on reference value. So, like in Fig. 9, only seven inputs, $u(k\text{-}1)$, $u(k\text{-}2)$, $u(k\text{-}3)$, $y(k)$, $y(k\text{-}1)$, $y(k\text{-}2)$, $y(k\text{-}3)$ are chosen as input of the neural controller except for reference $ref(k)$. Fig. 13 shows the response of the diesel engine speed control system from start to steady state.

In addition, impulse disturbance like in Fig.4 is added to system, and the dynamic characteristics of the diesel engine speed control system is investigated. Current neural controller was trained with training data obtained from the start to steady state without disturbance as seen in Fig. 10. When the system is stimulated by disturbance, neural controller does not work well and generate system hunting as shown by the Fig. 14. However, if the neural controller is trained using training data including disturbance and load condition, it tends not to be trained very well in whole area. In other words, the training stops with relatively

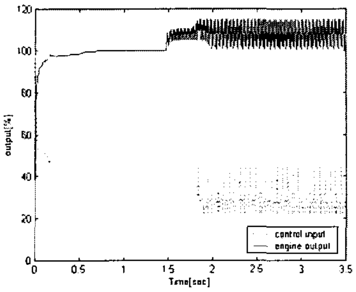

Fig. 14 The dynamic response characteristic of neural controller trained by training data not include disturbance data when the system is stimulated with impulse disturbance

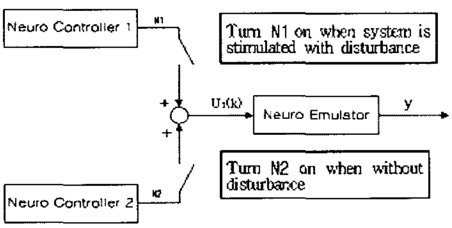

Fig. 15 Switching of the neural controller.

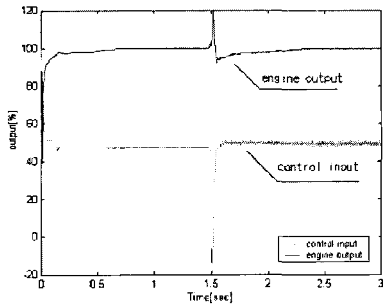

Fig. 16 The dynamic response characteristics of the engine in case of adding disturbance

large MSE. In order to solve this difficulties, this training data is divided into two parts; the part from start to steady state without disturbance and the disturbance part. Using these two kinds of training data, two neural controllers, that is, neural controller 1 and neural controller 2, are trained with respect to each part. After then, one of the two neural controllers is selected according

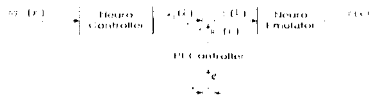

Fig. 17 Hybrid type neural control scheme with a PI compensator

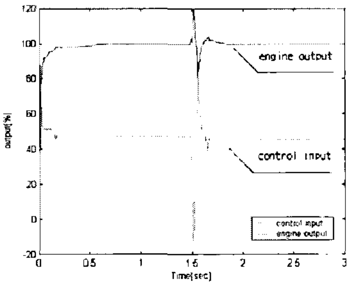

Fig. 18 The dynamic response characteristic of engine using proposed hybrid control system

to the operating environment as in Fig. 15.

The proposed neural controller shown in Fig. 15 performs appropriate operation for the disturbance like shown in Fig. 16. However, after the system is stimulated by disturbance, it takes long time to return to the reference. So, for rapid response control system is proposed shown in Fig. 17 PI compensator added.

In Fig. 17 NNs play a role as a main controller and the PI controller as a auxiliary controller. The PI controller is used to adjust control input u(k) for the plant to follow a desired reference ref(k) as precisely as possible. As shown in Fig 18, the response approaches the reference level faster than the control scheme using only a neural controller.

4. Conclusion

In this paper, neural emulator and neural controller for speed control system of diesel engine are proposed. To find out effective configuration of neural emulator for diesel engine, various kinds of backpropagation algorithm are compared. Among above mentioned three kinds of backpropagation algorithms, backpropagation algorithm using Levenberg- Marquardt optimization was proven to be most efficient for diesel engine identification. In order to improve the control performance, selective training method for neural controller is proposed and neural controller trained by this method was proven to follow real system efficiently even existing disturbance.

For fast response and exact following to the reference in the case of existing disturbance, hybrid control system which is combined with neural controller and conventional PI controller is proposed. Simulated results show that proposed hybrid control system controls efficiently speed of diesel engine driving electric generator in the case of existing disturbance.

In the future the study about developing dedicated controller implemented this hybrid neural control system and application to real diesel engine should be done.

후 기

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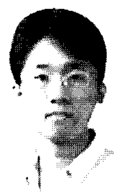

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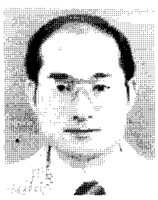

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