4.2 DEVELOPMENT OF A SURVEILLANCE SYSTEM FOR MAINTENANCE AND DIAGNOSIS OF BUSES BASED ON CAN-BUS DATA TRANSMITTED WIRELESSLY

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ABSTRACT

From the point of view of vehicle maintenance, one of the most important systems of urban buses is the cooling system. These vehicles run typically more than 80,000 km per year, and the radiator of the system gets fouled due to dust and dirt of the cooling air, which produces an increase in water temperature. This situation forces to stop the vehicle and perform washing of the radiator. This study is focused on the development of a model of the cooling system of urban buses based on an artificial neural network (ANN), which is used for system diagnosis and engine surveillance. Data are gathered from the CAN-bus system of every bus, which have allowed the development of a dynamic ANN that fits the cooling dynamics.

INTRODUCTION

For urban buses, energy consumption comes from the propulsion system, the auxiliaries, and the thermal management. The latter include the electric devices, the generator, and the cooling of the internal combustion engine (ICE). In this regard, maintenance of radiator takes out from service the bus and requires many hours of work and, therefore, is expensive from the maintenance point of view. If this issue is considered in a medium city transport company as the one of TUSSAM in Seville (Spain), with a fleet of more than 400 urban buses, the problem highlights because currently there is no procedure able to determine the state of the radiator.

STATE OF THE ART

From the point of view of energy consumption, thermal management is very relevant next to the rest of the energy fluxes inside a propulsion plant. The importance of considering thermal management as a procedure to reduce fuel consumption in ICE has been demonstrated (Caresana, Bilancia & Bartolini, 2011), where performance is not only to maximize fuel efficiency but to increase system life and reduce the maintenance cost (Bayraktar, 2012).

CONTRIBUTION

Cooling System

ICE has to operate below a temperature limit in order to guarantee performance and reliability. For this reason, the cooling system has to be properly maintained for the dissipation of the thermal energy generated by the whole vehicle. On the other side, the cooling system requires electrical energy for its duty. Therefore, the correct maintenance of this system contributes to the reduction of the energy consumption of the bus.

The cooling system includes two pumps arranged in series, a turbocharger heat exchanger, water radiators, a hydraulic fan, and several valves. Thermal energy from ICE (compressor, engine, gearbox, and retarder) is conducted by water through radiators, where it is transferred to ambient air by the fan, which has a maximum efficiency of roughly 50%. The regulation valve is managed by the temperature measured by three thermocouples that set the adequate water flow rate for any load, in order to guarantee that the maximum outlet temperature is below the limit for any operating condition.

ANN Modeling

ANNs are widely found in fields related to the diagnosis of internal combustion engines and system modeling, concretely for the detection and quantification of failures. The main reason is that they can learn the behavior of complex systems only from observations. On the other hand, ANN can be used as an inverse model (Desbazeille et al., 2010).

In this paper, only one ANN is necessary to determine system fault identification and its level and engine state, taking into account that the configured network is allowed to reproduce the output temperature of water of the engine block, gearbox, and retarder. With this porpoise, an ANN is configured, as well as trained and evaluated, in order to obtain a mapping between input variables and the corresponding output variables (targets). In this case, the input variables are as follows: instantaneous engine speed, ambient temperature, instantaneous engine torque, and instantaneous fuel consumption. On the other side, the output variables are the instantaneous temperature of the leaving water from the engine block, the output temperature of the retarder, and the gearbox.

ANN Architecture and Training Method

Since the relationship between inputs and targets is highly nonlinear, a multi-layer network has been chosen. The transfer function in the hidden layers is the tangent sigmoid function and the function for the output layer is linear. Such a network structure is considered a universal function approximator (Hornik, Stinchcombe & White, 1989). In this case, the forward function is obtained directly from data, so the configured ANN has to learn the inverse relationship. As the number of hidden layers is concerned, one hidden layer has been chosen. The number of neurons in this layer is 19 and has been obtained by trial and error.

Regarding the training method, the Levenberg–Marquardt algorithm has been used. In this kind of training method, early stopping must be taken into account to avoid the unwanted overfitting effect. Because of this, the total sample data has been divided into three groups: training set (60% of the data), test set (20% of the data), and the mentioned validation set (20% of the data).

Input and Target Data

Through the cooling system data gathered of the CAN bus, a set of ANN inputs and targets have been specified. Such a set must be a representative sample of the engine's whole load, which includes winter, spring, autumn, and summer data. This is important due to the huge change of ambient temperature and the engine load that change the thermal load on the cooling system. Holidays have also been included because the load of the bus is greatly reduced on these days. The performance of the ANN has been evaluated by means of a set of data that is not used throughout the training process, that is, the aforementioned validation set. A useful tool for the ANN validation test is the relationship between the targets and outputs. In this case, a linear relationship has been observed, which means a regression coefficient close to 1. This means that no overfitting takes place and, as a result, it can be considered that the trained ANN has achieved favorable results.

Noise Effect

In order to verify the robustness of the dynamic ANN against noise, random noise has been added to the signals coming from the input data. Two different noise signals have been considered:

Noise characterized by mean = 0 and standard deviation = 1.5%

Noise characterized by mean = 0 and standard deviation = 3.0%

The trained ANN outputs were compared to the targets and a lack of robustness could be observed. However, after a sensitivity analysis, it has been seen that the most affected signal was room temperature, having the rest low sensitivity to noise. In this regard, both sensor accuracy and position are considered to be relevant for the robust results of the cooling model.

CONCLUSIONS

A complete procedure for modeling the cooling system of an urban bus has been developed. The method is based on the integration of instantaneous CAN-bus data and a multilayer dynamic ANN. The method presents high robustness and also showed its capability for diagnosing the health of the engine oriented to preventive maintenance and failure diagnosis.

The method will be applied to a fleet of 20 urban buses that belong to TUSSAM, where it will be used for monitoring the condition of the cooling system. A huge reduction of the fleet out-of-service period is expected due to maintenance duties and an increase in fleet availability.

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