ARTIFICIAL NEURAL NETWROKS-BASED MODELING FOR ELECTRICAL ACTUATED AUTOMOTIVE COOLING SYSTEMS

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ABSTRACT

In this study, artificial neural network-based models for electrical actuated automotive cooling systems are developed and analyzed. The proposed models are constructed to represent the dynamical behavior of advanced automotive cooling systems. Three types of artificial neural networks (ANNs) are constructed; MPL, Elman, and NARX networks where experimental data are utilized in the development process of the models. The proposed ANN models are developed and tested in simulation to approximate the performance of the actual system. Statistical results are demonstrated to show the effectiveness of the proposed ANNs.

1. INTRODUCTION

Advanced automotive cooling systems can significantly improve the response of gasoline and diesel engine and better enhance its temperature regulation, minimize fuel consumption, and reduce parasitic losses along with tailpipe emissions [1-3]. Embedding computer-controlled water pump, radiator fan, and variable position smart valve into the vehicle cooling system increases the system efficiency in comparison with the conventional cooling system [4, 5]. In advanced automotive cooling systems, the mechanical water pump and radiator fan are replaced with electrically driven actuators [6] or hydraulically driven actuators [7] for a single loop cooling system [8] or a multiple-loop cooling system [9].

Modeling of automotive cooling systems is essential to study the system response and performance thoroughly. Wagner *et al.* [10] introduced a lumped parameter and multi-node thermal models to estimate the temperature of internal combustion engine. In [11], Eberth *et al.* proposed mathematical and empirical models to represent the dynamics of a 4.6L spark ignition engine and to describe the smart cooling system components. In fact, modeling of cooling systems is necessary to avoid the high cost of hardware builds and long testing hours. Henry *et al.* [12] developed a simulation model of cooling systems for ground vehicles and showed that different thermal management control ideas can be investigated to the feasibility in improving fuel economy and/or emissions of the vehicle.

Most of the above literature is based on developing nonlinear mathematical models for the automotive cooling systems. However, neural networks (NNs) can be utilized to develop the nonlinear model since they show great ability in modeling highly nonlinear dynamic systems. Because of the ability to model nonlinear functions and to learn from input-output data, NNs have been used in many applications, such as function approximation, classification, data processing, systems identification, and control.

In [13], Yusuf *et al.* utilized artificial neural networks (ANNs) to predict the performance of a spark ignition engine that operates using methanol and gasoline. They found out that the developed ANN model was practically able to estimate the fuel consumption and exhaust emissions. In [14], an ANN was applied on diesel engine powered with diesel fuel, biodiesel, B20, and bioethanol with diesel fuel having different percentages (5%, 10%, and 15%). The applied ANN was used to estimate the power, moment, and fuel consumption. The authors of [14] demonstrated the effectiveness of the developed ANN model when compared with experimental data. Reliability value was calculated to be 99.94% utilizing statistical analyses.

Najafi *et al.* [15] conducted a comprehensive combustion analysis to evaluate the performance of a commercial Direct Injection (DI) engine, using waste vegetable cooking oil as an alternative fuel. The authors developed an ANN based on experimental data. Their developed model showed that the training algorithm of back propagation was sufficient to predict the engine torque, fuel consumption, and exhaust gas components for different engine speeds and fuel blends ratios.

Parlaka *et al.* [16] studied the ability of an ANN-based modeling, with a back propagation learning algorithm, to predict specific fuel consumption and exhaust temperature of a diesel engine. The authors compared the develop ANN with experimental data and showed that the model behaved satisfactorily. It is considered that a well-trained neural network model provides fast and consistent results, making it an easy-to-use tool in preliminary studies for such thermal engineering problems.

In this paper, artificial neural networks (ANNs) are utilized to estimate the dynamical model of electrical actuator automotive cooling systems. The main goal is to explore new methods of modeling for automotive thermal systems and to investigate the system performance utilizing such modeling approaches.

2. COOLING SYSTEM MATHEMATICAL MODEL

Cooling systems of internal combustion engines (ICEs) can be represented by a simplified reduced order two-node lumped parameter thermal model as shown in Figure 1. The engine and radiator temperature dynamics can be represented as [8]

$$C_e \dot{T}_e = Q_{in} - c_{pc} \dot{m}_r \left(T_e - T_r\right) \tag{1}$$

$$C_r \dot{T}_r = -Q_o + c_{pc} \dot{m}_r \left(T_e - T_r\right) - \varepsilon c_{pa} \dot{m}_f \left(T_e - T_\infty\right) \tag{2}$$

where $C_e, C_r, c_{pc}, c_{pa}, T_e(t), T_r(t), T_\infty(t), \dot{m}_r(t)$, and $\dot{m}_f(t)$ are the engine capacity, radiator capacity, coolant specific heat, air specific heat, coolant temperature at the engine outlet, coolant temperature at the radiator outlet, surrounding ambient temperature, radiator coolant and fan air mass flow rates, respectively.

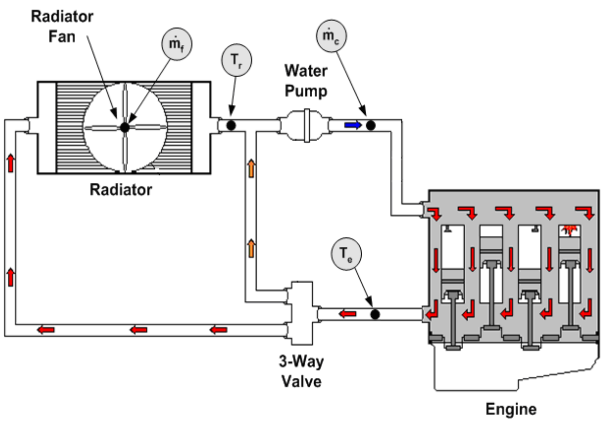


Figure 1. *Laboratorial automotive cooling system*

The variables $\dot{m}_r(t)$ and $\dot{m}_f(t)$ are the control inputs for the system. It should be noted that the radiator coolant mass flow rate, $\dot{m}_r(t)$, can be expressed in terms of the pump coolant mass flow rate, $\dot{m}_c(t)$, and normalized valve position, $H(t)$, such that $\dot{m}_r = H\dot{m}_c$ where the condition $0 \le H \le 1$ is satisfied. Note that $H = 1$ corresponds to a fully closed valve position and coolant flow through the radiator loop and $H = 0$ corresponds to a fully open valve position and coolant flow through the bypass loop. For electrical actuated cooling systems, the variables $\dot{m}_c(t)$ and $\dot{m}_f(t)$ are generated by electrical coolant pump and fan, respectively. Hence, the mass flow rates are controlled by electrical signals as desired. The input heat generated by the combustion process which is transferred to the coolant through the engine's water jacket is represented by the variable $Q_{in}(t)$. The radiator heat loss due to uncontrollable air flow is represented by the variable $Q_o(t)$. Finally, ε denotes the radiator efficiency.

3. APPLICATION OF ARTIFICIAL NEURAL NETWORKS ON THE EXPERIMENTAL DATA

ANNs are computational models that can be used to imitate the behavior of biological networks. Such models are used to solve complex functions in diverse applications [17]. In general, ANNs consists of three layers: (i) input layer, (ii) hidden layer(s), and (iii) output layer [18]. Each layer may have as many as needed of computational hidden nodes or neurons [19]. The advantages of using ANNs are speed, simplicity and ability to train past data to provide the necessary predictions. ANN has been utilized in a wide range of applications such as recognition, optimization, clustering, regression, and prediction.

An ANN is trained by introducing different known input and desired output vectors. The weights of the ANN are updated in order to reduce difference between the ANN actual output and desired one. When desired accuracy is obtained, training stops and then the ANN is tested by using different data other than the one used in the training step. More details about these steps can be found in [18].

In this study, three types of ANN (*i.e.*, Multilayer Perceptron (MLP), Elman, and NARX networks) are constructed and tested in simulation utilizing experimental data from [8]. The MLP is a multilayer feedforward neural network, where the data only moves from input layer to hidden layer and from hidden layer to output layer; no data are fed back to other layers. The Elman neural network is a recurrent neural network and very similar to the MPL neural network except it has a feedback from the hidden layer output back to the input layer. This structure is useful in detecting and generating time-varying patterns. The main feature of Elman networks is that they store values from the previous time step, which can be used in the current time step. On the other hand, NARX neural networks are recurrent dynamic networks, with feedback connections enclosing several layers of the network. NARX networks can be used as predictors, nonlinear filtering, and modeling of nonlinear dynamic systems. More details about these three ANNs can be found in [20]. MATLAB and its Neural Network toolbox were utilized to verify the performance of the three ANNs in modeling the dynamic model of the automotive cooling system depicted in Figure 1. In the ANN models, the engine and radiator temperatures are estimated given the inputs as shown in Figure 2. Three ANNs are implemented to model the system depicted in Figure 1. The experimental data in [8] are utilized to train the ANNs. Table 1 shows the training parameters with their values.

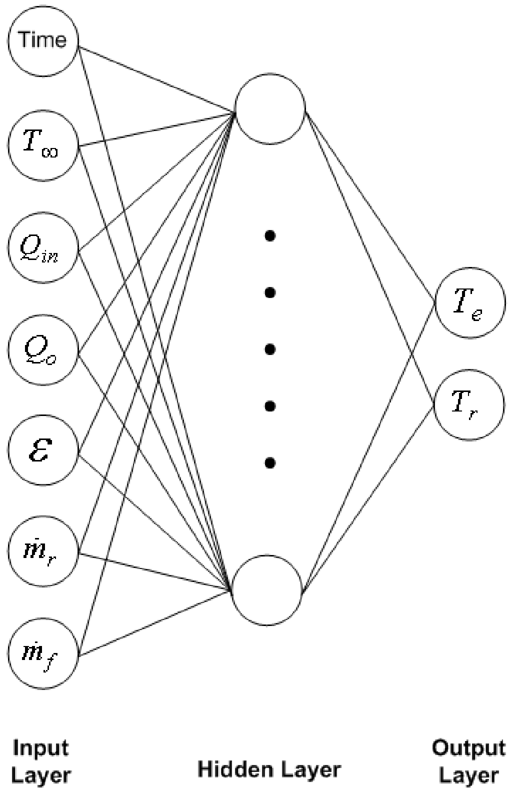


Figure 2. *Inputs and outputs of the proposed ANNs.*

TABLE 1: TRAINING PARAMETERS FOR ANNS

Parameter	Value
Epochs between displays	1
Maximum number of epochs to train	1000
Maximum time to train in seconds	∞
Performance goal	0
Maximum validation failures	6
Factor to use for memory/ speed Tradeoff	1
Minimum gradient error	1×10^{-5}

The three types of ANNs were constructed and tested in simulation, where number of neurons in hidden layer for MPL, Elman, and NARX were 2, 7, and 10, respectively. A total of 400 data points from the experimental tests in [8] were utilized to train the proposed ANNs. The 400 data points were divided into three parts, 40% of available data was utilized for training, 30% was utilized for validation, and 30% was utilized for testing. Tangent sigmoid function was used in hidden layer, and linear transfer function was used in the output layer.

The performance of the developed ANNs is investigated using three global statistics; coefficient of determination (R), root mean squared error (RMSE), and mean bias error (MBE) as shown in the following expressions

$$R = 1 - \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \tag{3}$$

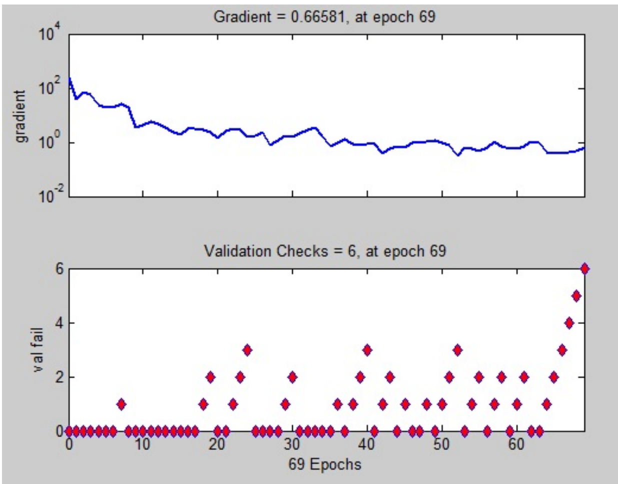
$$RMSE = \sqrt{\frac{\sum_j (t_j - o_j)^2}{p}} \tag{4}$$

$$MBE = \frac{\sum_j (t_j - o_j)}{p} \tag{5}$$

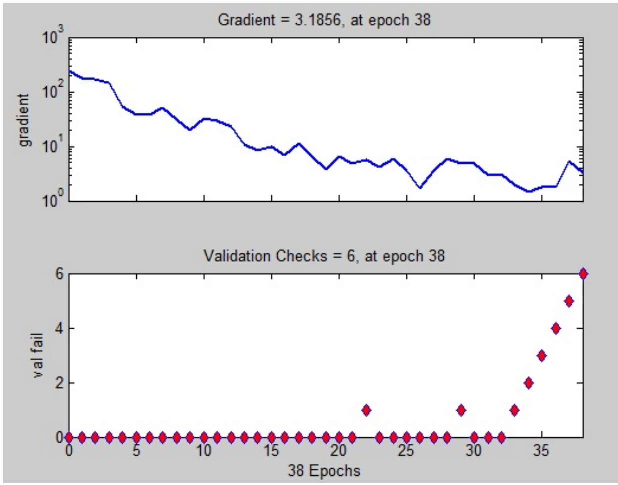
where R is a measure used in statistical model analysis to evaluate the prediction performance for future outcomes, t_j is the target value, and o_j is the output value. By increasing the value of R, more accuracy of the model can be obtained. The RMSE is a quadratic scoring rule that measures the average magnitude of the error, where p is the pattern. The MBE is a measure of overall bias error or systematic error. By reducing the value of the MBE, more accuracy of the model can be obtained.

4. RESULTS AND DISCUSSIONS

In MLP ANN, the training was stopped after 69 epochs. On the other hand, the training was stopped after 38 epochs, in Elman network, and after 149 epochs, in NARX network. The magnitude of the gradient error and the number of validation checks are used to evaluate the ANNs performance. During training, the gradient error decreases until training termination conditions are met. The number of validation checks represents the number of successive iterations at which the validation performance fails to decrease the gradient error further. Variation of the gradient error and validation checks at each epoch are shown in Figure 3 for all the three ANNs. The gradient error at the end of the training for the MLP, Elman, and NARX were 0.666, 3.18, and 0.167, respectively. Scatter plot of training, validation, testing experimental data, and the three ANN outputs are shown in Figure 4. NARX showed the best data performance and fit between ANN output and desired output as shown in Figure 4, where R for training, validation, and testing data are 0.99973, 0.9993, and 0.99924, respectively. Figures 5 and 6 Show the engine and radiator temperature responses with the three ANNs versus the experimental response for a step input. Once more, the NARX ANN showed the best fit to the experimental data. Table 2 lists the performance of the three ANNs in terms of R, RMSE, and MBE. Best values for R, RMSE, and MBE were obtained with the NARX ANN.



(a)



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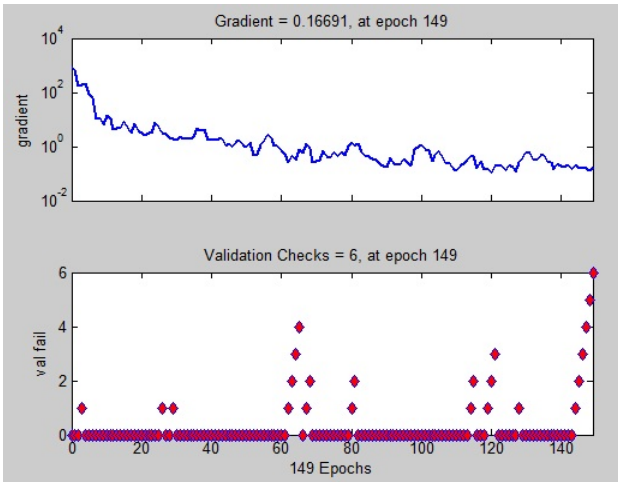
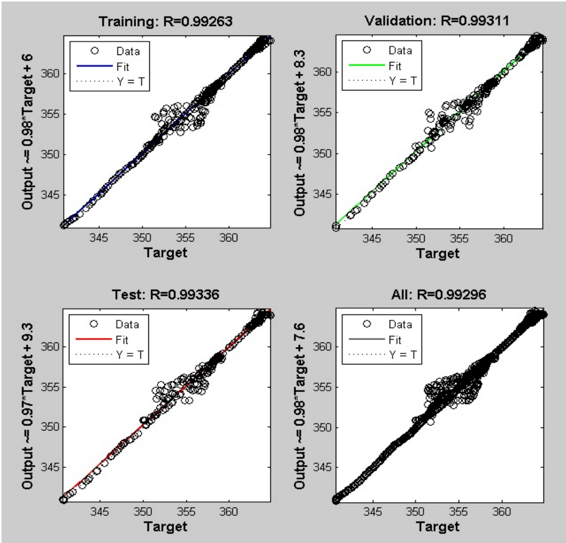
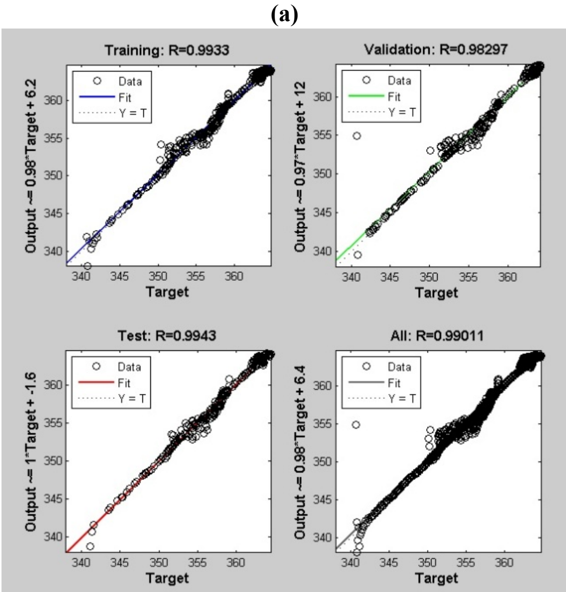


(c)

Figure 3. *Variation of gradient error and validation checks for (a) MLP Network (b) Elman Network, and (c) NARX Network.*



(a)



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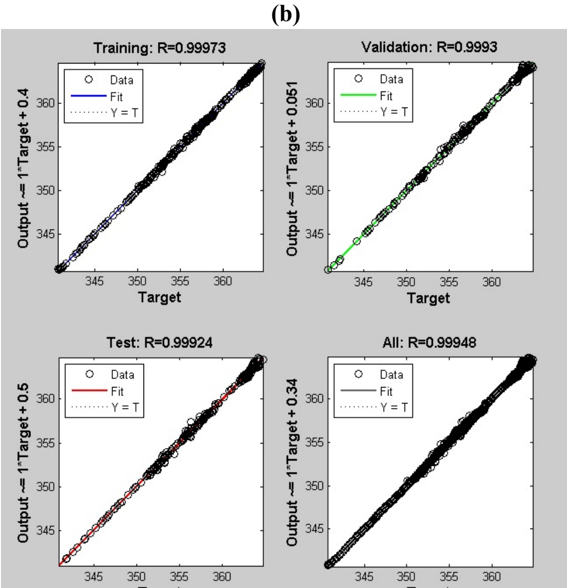

(c)

Figure 4. *Scatter plot of training, validation, testing for (a) MLP Network, (b) Elman Network, and (c) NARX Network.*

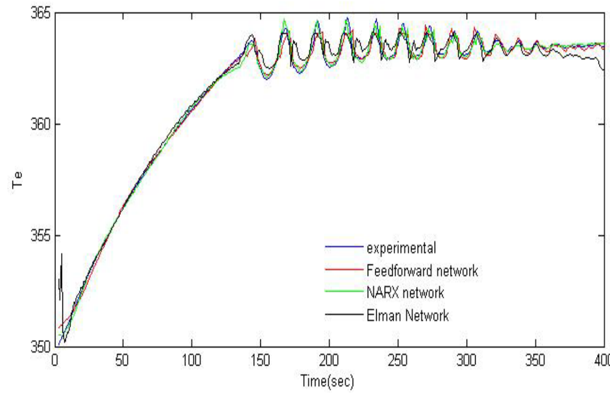

Figure 5. *Experimental and estimated engine temperature responses for a step input.*

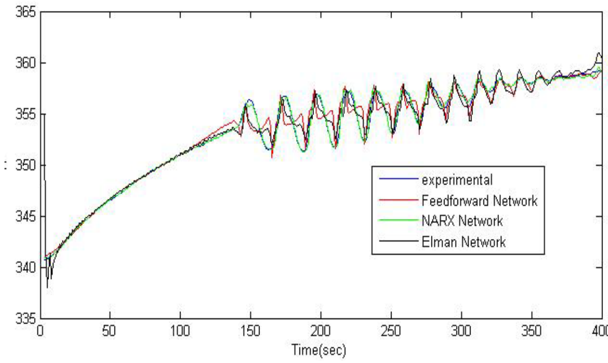

Figure 6. *Experimental and estimated radiator temperature responses for a step input.*

TABLE 2: PERFORMANCE OF THE THREE ANNS

		MLP	Elman	NARX
R	Training	0.99263	0.9933	0.99973
	Validation	0.99311	0.98297	0.9993
RMSE	Training	0.7117	0.6650	0.1424
	Validation	0.6774	1.1354	0.2092
MBE	Training	0.3706	0.4518	0.1008
	Validation	0.3839	0.4917	0.1368

5. CONCLUSION

Three types of artificial neural networks (*i.e.*, MLP, Elman, and NARX) are proposed, developed, and tested to imitate the behavior of electrical actuated automotive cooling systems. Experimental data are utilized in the development process of the ANN models to estimate the actual performance of dynamic model in simulation. Statistical methods are utilized as well to demonstrate the effectiveness of the proposed ANNs. The numerical results show that NARX neural networks performs better than other ANNs although they demonstrate satisfactory performance.

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