24th AGM & International Conference of the Nigerian Institution for Mechanical Engineers (NIMechE)

Hosted by the Nigerian Institution for Mechanical Engineers
Lagos, Nigeria October 12-14, 2011

PREDICTION OF FRICTION LOSSES IN SPARK-IGNITION ENGINES: AN ARTIFICIAL NEURAL NETWORKS APPROACH

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ABSTRACT Multi-layered, feed-forward, back-propagation artificial neural networks (ANN) models were developed to predict friction losses in spark-ignition engines. The friction losses were modeled as friction mean effective pressure (fmep) due to: crankshaft, reciprocating parts, valve trains, auxiliary, and pumping systems. The developed models were validated in relation to existing engine friction data and empirical models of Patton et al. (Patton, K.J., Nitsche, R.G. and Heywood J.B. [1989]. Development and evaluation of a friction model for spark-ignition engines, SAE paper 890836). Results have shown that, the mean absolute deviations of the ANN model predictions for crankshaft, reciprocating parts, valve trains, auxiliary, and pumping systems were, respectively, 18.78, 2.10, 10.57, 2.66, and 8.84% in relation to the existing engine friction data, while those of the Patton et al. model predictions were 37.50, 25.14, 60.99, 6.71, and 14.67%, respectively. The corresponding root mean square errors were found to be 2.278, 1.157, 3.145, 0.678, and 2.118 for the ANN predictions and 7.006, 12.837, 15.889, 2.277, and 3.317, respectively, for the Patton et al. predictions. The developed ANN friction models appeared to have better and more accurate predictions, thus it could be used as tool for designing of energy-efficient spark-ignition engines.

Keywords: Artificial neural networks, friction losses, spark-ignition engines, energy-efficient

INTRODUCTION Engine friction is commonly defined as the difference between indicated work done by the working fluid on the piston and the brake work measured as output at the crankshaft. It accounts for a considerable proportion of energy loss in engines, causes wear of engine parts, reduces brake power and mechanical inefficiency, and increases fuel consumption and greenhouse gas emissions (Basshuysen et al., 2004; Faires et al., 1957; Fujii et al., 1988; Lumley et al., 1999; Obert, 1948; Oyadotun, 2002). The development of appropriate and accurate techniques for estimating engine friction and its reduction have been major challenges faced by engines designers in the development of new energy-efficient engines (Patton et al., 1989). Studies on engine friction have a long history, going back to the time of Leonardo da Vinci. Luminaries of science such as Amontons, Coulomb and Euler were also involved in engine friction studies, but there is still no simple model which could be used by designers to calculate the frictional loss for a given pair of materials in contact. Development of new energy-efficient engines therefore necessitates the development of appropriate techniques or strategies for modeling and estimation of engine friction losses. For efficient modeling and estimation of friction losses in engines, accurate and adequate knowledge of the underlying relationships between the friction parameters and the design and operating parameters of the engine are essential. Pioneering studies of these underlying relationships have been mainly focused on the development of appropriate mathematical relations such as analytical or empirical models (Rosenberg, 1982; Bishop, 1965; Oetting, 1982; Boshi et al., 1986; Uras, 1984; Amann, 1988; Betz et al., 1986; Armstrong et al., 1981; Staron et al., 1983; Millington et al., 1968; Gish, 1958). In particular, the work of Patton, (1989) was on the development of empirical models based on combination of fundamental scaling laws and empirical results for prediction of rubbing losses from the crankshaft, reciprocating, and valve-train components, auxiliary losses from engine accessories, and pumping losses from the intake and exhaust systems. The inherent limitations and complication of this developed empirical friction model led to development of an improved version of the model by Sandoval and Heywood (Sandoval et al., 2003). However, all the developed mathematical models are complex and hence the setting up of the parameters and how they interrelate entirely depends on the vast experience and intuition of the modeler and so many of the developed models have inherent deficiencies in adequately and correctly representing the relationships between engine friction and the design and operation parameters of the engine. As a possible solution to handling of these complexities, the use of experimental investigation has also being proposed by many investigators (Lancasteret et al., 1975; Adams et al., 1987; Ino, 1984). However, experimental setup involving all of the underlying factors between friction components, engine design and operating parameters is cumbersome, time consuming and costly to implement. Hence, experimentations are limited in scope and application in engine friction studies. These limitations in the developed mathematical models are better handled using artificial neural networks modeling techniques (Avula, 2002).

The artificial neural networks (ANN) approach provides a viable solution in mitigating the complexities in developing mathematical models. At present, ANN is emerging as the technology of choice for many applications such as pattern recognition, system identification and control (Mellit et al., 2006; Fadare, 2009). ANN is a branch of Artificial Intelligence (AI) and is an intelligent data-driven modeling tool that is able to capture and represent complex and non-linear input/output relationships that cannot be captured by traditional statistical methods such as regression which may only be efficient in handling cases where the variables have linear relationship (Stitch et al., 2000; Cavuto, 1997). ANN has been applied to spark-ignition engines to model the torque, specific fuel consumption, brake power, output torque and exhaust emissions (Glcn et al., 2005; Yncesu et al., 2007; Deh-Kiani et al., 2010; Kara, et al., 2010). However, to the best of the authors' knowledge, there is no study reported in literature on the application of ANN model for prediction of friction losses in spark-ignition engines.

The objective of this present study was to apply ANN in the development of engine friction mean effective pressure models for modeling and prediction of crankshaft, reciprocating, valve, auxiliary and pumping friction losses in spark-ignition engines. The proposed ANN friction models can be used as an efficient tool by engine designers for the design and performance assessment of spark-ignition engines for energy efficiency.

MATERIALS AND METHODS

Assembly and preprocessing of dataset. The data used in this study were obtained from two sources: (1) the friction models developed by Patton et al. (1989) were used to generate the dataset for forty in-line spark-ignition engines from the Bosch Automotive Handbook (Bosch, 2007). The design parameters of the engines are given in Table 1. The dataset were generated for engine speeds ranging from 500 to 7500 rpm, and (2) experimental data of some selected engines were obtained from existing literature. The dataset assemblage was done for each engine friction component; crankshaft, reciprocating group, valve group, auxiliary group and pumping group. For the development of the friction models, 606 dataset were used for the crankshaft friction model, 608 for the reciprocating friction model, 612 for the valve friction model, 762 for the auxiliary friction model and 608 for the pumping friction model. The dataset for each friction component was normalized to range between -1 and +1 and then partitioned into training (50%), testing (25%) and validation dataset (25%).

Design of the ANN model. Multi-layer, feed-forward, back-propagation hierarchical networks with different structures were designed using the Neural Network Toolbox for MATLAB® 7.0 (R14). The models consisted of three layers of neurons: "input layer", "hidden layer" and "output layer" (Figure 1). The choice of input/output parameters of the friction component models was based on the parameters used in the Patton et al's model, while the number of neurons in the hidden layer was varied ranging from 5 to 20 in steps of 5 to determine the optimum structure of the network required for each friction component model. The input/output parameters of the models are given in Table 2.

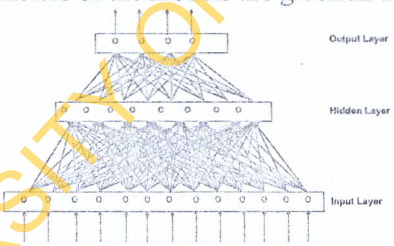

Fig. 1: Typical multilayered ANN with (13-8-4) structure

Training and testing of the neural network models. Three back-propagation learning algorithms were investigated for each of the friction component: Levenberg Marquard (LM), Scaled conjugate gradient (SGC) and Resilient back propagation (RP). The early stopping technique was used to improve generalization capability of the network and to prevent the network from over-fitting the training dataset. Over-fitting occurs when the network becomes too used to the training dataset and thus fails in predicting other data outside the training dataset (Demuth et al., 2000)

The training process was terminated when the threshold of MSE = 0.001 or when the number of iterations equal to 1000 was attained. The mean-square error (MSE) and the correlation coefficient (R-value) between the actual and ANN predicted values of the friction mean effective pressure were used to determined the predictive accuracy of the network models. The best network structure and learning algorithm for each friction component model was determined based on lowest MSE value, number of iterations and highest R-value.

RESULTS AND DISCUSSIONS

Optimization of network parameters. The performance indicators in terms of the MSE value, number of iterations and R-value were used to determine the optimum network parameters of the different friction component model. The best network structure for each model is shown in Tables 2.

Model Validation

Crankshaft friction model. For the crankshaft friction model, a comparison between the experimental data, Patton, K. J et al's model predictions and ANN predictions was made for a Ford 1.6l. The result of the comparison is presented in Figure 3. As shown in Figure 3, the Patton et al.'s model predictions and the experimental data agreed quite well only at engine speeds ranging from 500 - 2000 rpm and deviated widely at speed range beyond 2000 rpm. The mean absolute deviation of the Patton, et al's predictions from the actual data was 37.50%. However, the ANN predicted values and the experimental data showed better agreement for the entire speed range considered with mean absolute deviation of 18.78%. The root mean square errors of the Patton et al.'s and ANN predictions were respectively 7.006 and 2.278.

Reciprocating friction model. The comparison between the experimental data, Patton, K. J et al's model predictions and ANN predicted values are shown in Figure 4. The Patton, K. J et al's model predictions were consistently higher than the experimental data with mean absolute deviation of 25.14%, while the corresponding value of 2.10% was obtained for the ANN predictions. The root mean square errors of the Patton et al.'s and ANN predictions were respectively, 12.837 and 1.157.

Valve friction model. Figure 5 shows the comparison between the experimental data, Patton et al.'s model predictions and ANN predicted values for the valve friction of a new dataset for a Ford 2.3l engine. The mean absolute deviation of Patton et al's model predictions and the ANN predictions from the experimental values were 60.99 and 10.57%, respectively. The root mean square errors of the Patton et al's and ANN predictions were respectively 15.889 and 3.145.

Auxiliary friction model. In validating the auxiliary group friction model, datasets for a Volkswagen 1.3l engine and the Patton et al's model predictions and the ANN predictions were compared with the experimental data (Figure 6). Patton et al's model and the ANN model predicted the auxiliary friction with high degree of accuracy and mean absolute deviation of 6.71 and 2.66%, respectively. The root mean square errors of the Patton, K. J. et al.'s and ANN predictions were 2.277 and 0.678, respectively.

Pumping friction model. In validating the pumping group friction model, dataset for a Volkswagen 1.6l engine and corresponding values of mean absolute deviation of 14.67 and 8.84%, respectively were obtained for the Patton et al.'s model and the ANN model predicted values (Figure 7). The respective root mean square errors of the Patton et al.'s and ANN predictions were 3.317 and 2.118.

Table 1: Design parameters of the engines used to generate the friction data using the Patton et al. models

S/N	Vehicle/Engine make	Compression Ratio	Bore, (mm)	Stroke, (mm)	No. of cylinder	No. of valves	Sweep volume. (cm^3)
1	Mazda AZ Wagon 0.7Ti	10.5	65	66	3	12	657
2	Toyota Yaris 1.0i	10	69	66.7	4	16	998
3	Opel Astra 1.2i	10.1	72.5	72.6	4	16	1199
4	Daihatsu Charade 1.3i	9.5	76	71.4	4	16	1296
5	Mazda Demio 1.3i	9.4	71	83.6	4	16	1324
6	Ford puma 1.4i	10.3	76	76.5	4	16	1388
7	Polo 1.4	10.5	76.5	75.6	4	16	1390
8	Rover 214 1.4i	10.5	75	79	4	16	1396
9	Honda Civic Aerodeck 1.5i	9.6	75	84.5	4	16	1493
10	Mazda 323P 1.5i	9.4	78	78.4	4	16	1498
11	Fiat Multipla 1.6i Bipower	10.5	86.4	67.4	4	16	1581
12	Honda HR-V 1.6i	9.6	75	90	4	16	1590
13	Ford Escort 1.6	10.3	76	88	4	16	1597
14	Alfa Romeo 145 1.6i TS	10.3	82	75.65	4	16	1598
15	Fiat Bravo 1.8i	10.3	82	82.7	4	16	1747
16	Renault Laguma Break 1.8i	9.8	82.7	83	4	16	1783
17	Mitsubuishi Carisma 1.8 GDi	12.5	81	99	4	16	1834
18	BMW Z 31.9	10	85	83.5	4	16	1895
19	Hyundai Coupe 2.0i	10.3	82	93.5	4	16	1975
20	Seat Cordoba 2.0i	10.5	82.5	92.8	4	16	1984
21	Ford Mondeo 2.0	10	84.8	88	4	16	1988
22	Mazda 626 Wagon 2.0i	9.7	83	92	4	16	1991
23	Lancia Delta 2.0 Turbo HPE	8	84	90	4	16	1995
24	Chrysler Sebring 2.0i	9.6	87.5	83	4	16	1996
25	Peugeot 206 2.0i	10.8	85	88	4	16	1997
26	Lexus IS 200 2.0i	9.6	75	75	6	24	1988
27	Mercedes-Benz CL 500	8.5	89.9	78.7	4	16	1998
28	Toyota Picnic 2.0i	9.5	86	86	4	16	1998
29	Mercedes-Benz SLK 200	10.4	89.9	78.7	4	16	1998
30	Opel Astra 2.0i	10.8	86	86	4	16	1998
31	Opel Sintra 2.2i	10.5	86	94.6	4	16	2198
32	Mercedes-Benz SLK 230 compressor	8.8	90.9	88.4	4	16	2295
33	Volvo C70 2.3i	8.5	81	90	5	20	2319
34	Oldsmobile Alero 2.4i	9.5	90	94	4	16	2392
35	Dodge Caravan 2.4i	9.4	87.5	101	4	16	2429
36	Volvo V70 2.4i	10.3	83	90	5	20	2435
37	BMW 323i Touring	10.5	84	75	6	24	2494
38	Volvo S80 2.8 T6	8.5	81	90	6	24	2783
39	BMW 328i	10.2	84	84	6	24	2793
40	Lexus GS 300 3.0i	10.5	86	86	6	24	2997

Table 2: Optimum network parameters of the friction component models

Model	Input parameters	Output parameter	Network Structure	Training Algorithm	No. of iterations	Correlation coefficient	MSE
Crankshaft Friction	(1) Diameter of main bearing; (2) Bore; (3) Stroke; (4) Number of cylinders; (5) Engine speed; (6) Length of main bearing; (7) Number of main bearings	(1) Crankshaft friction mean effective pressure	7-20-1	LM	4	1.000	0.004
Reciprocating Friction	(1) Mean piston speed; (2) Bore; (3) Engine speed; (4) Diameter of reciprocating bearing; (5) Length of reciprocating bearing; (6) Number of main bearings; (7) Number of cylinders; (8) Intake manifold pressure; (9) Atmospheric pressure; (10) Compression ratio; (11) Stroke; (12) Reciprocating group exponent	(1) Reciprocating friction mean effective pressure	12-10-1	RP	50	0.756	0.006
Valve Friction	(1) Engine Speed; (2) Number of shaft bearings; (3) Bore; (4) Stroke; (5) Number of cylinders; (6) Number of valves; (7) Maximum valve lift; (8) Coefficient for oscillatory hydrodynamic; (9) Coefficient for mixed hydrodynamic	(1) Valve friction mean effective pressure	9-15-1	LM	26	1.000	0.003
Auxiliary Friction	(1) Engine Speed	(1) Auxiliary friction mean effective pressure	1-15-1	LM	100	1.000	2.119×10^{-010}
Pumping Friction	(1) Atmospheric pressure; (2) Intake manifold pressure; (3) Mean piston speed; (4) Number of valves; (5) Intake valve diameter per bore; (6) Exhaust valve diameter per bore; (7) Coefficient for roller follower; (8) Coefficient for oscillating hydrodynamic; (9) Coefficient for oscillatory mixed	(1) Pumping friction mean effective pressure	9-10-1	LM	83	0.996	13.387

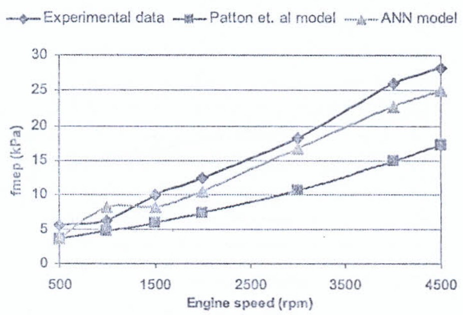

Fig. 3: Comparison between experimental, Patton et al's model and ANN predicted values for crankshaft friction of a Ford 1.6l engine

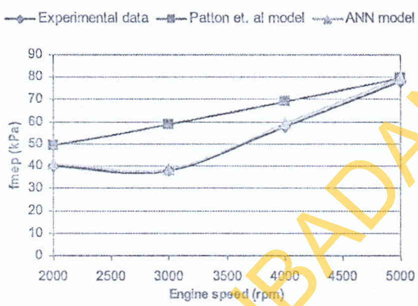

Fig. 4: Comparison between experimental data, Patton et al's model and ANN prediction for reciprocating friction using a Malhe 86 x 83.5 engine

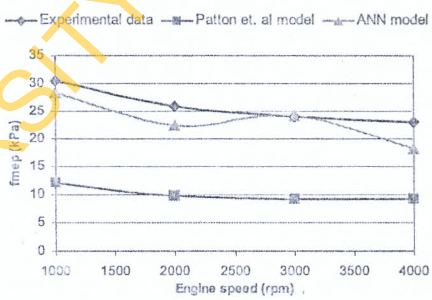

Fig. 5: Comparison between experimental data, Patton et al's model and ANN predictions of valve friction for a Ford 2.3l engine

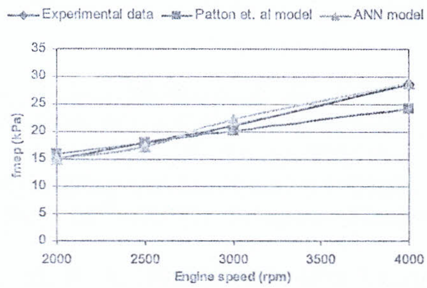

Fig. 6: Comparison between experimental, Patton et al's model and ANN predictions of auxiliary friction for a Volkswagen 1.3l engine

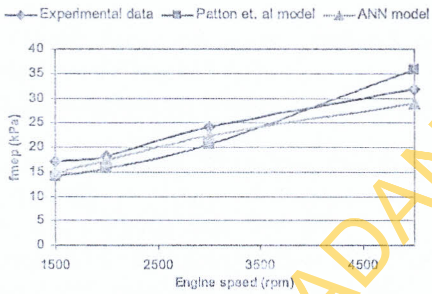

Fig. 7: Comparison between experimental, Patton et al model and ANN model of pumping group friction for a Volkswagen 1.6l engine

CONCLUSION. Multi-layer, feed-forward, back-propagation hierarchical neural networks with different structures were designed using the Neural network toolbox for MATLAB® 7.0 to model and predict the friction mean effective pressure (fmep) due to: crankshaft, reciprocating parts, valve trains, auxiliary, and pumping systems in spark-ignition engines. In training of models, the predictive performance of three (3) learning algorithms: Levenberg Marquard (LM), Scaled conjugate gradient (SGC), and Resilient back propagation (RP) were investigated. The LM algorithm-trained models gave more accurate predictions except for the reciprocating friction model where the RP algorithm gave the best predictions. The mean absolute deviations of the ANN model predictions for crankshaft, reciprocating parts, valve trains, auxiliary, and pumping systems were, respectively, 18.78, 2.10, 10.57, 2.66, and 8.84% in relation to the existing engine friction data, while those of the Patton et al. model predictions were 37.50, 25.14, 60.99, 6.71, and 14.67%, respectively. The corresponding root mean square errors were found to be 2.278, 1.157, 3.145, 0.678, and 2.118 for the ANN predictions and 7.006, 12.837, 15.889, 2.277, and 3.317, respectively, for the Patton, K. J. et al. predictions. Hence, the developed neural networks models have great prowess in understanding the underlying input and output relationships and so are excellent tools for developing reliable engine friction models.

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