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Development and Validation of a Model for Mechanical Efficiency in a Spark Ignition Engine

Ivan Arsie, Cesare Pianese, Gianfranco Rizzo
Department of mechanical Engineering, University of Salerno, Italy

Roberto Flora, Gabriele Serra
Magneti Marelli, Engine Control Division, Bologna, Italy

ABSTRACT

A set of models for the prediction of mechanical efficiency as function of the operating conditions for an automotive spark ignition engine is presented. The models are embedded in an integrated system of models with hierarchical structure for the analysis and the optimal design of engine control strategies. The validation analysis has been performed over a set of more than 400 steady-state operating conditions, where classical engine variables and pressure cycles were measured. Models with different functional structures have been tested; parameter values and indices of statistical significance have been determined via non-linear and step-wise regression techniques. The Neural Network approach (Multi Layer Perceptrons with Back-Propagation) has been also used to evaluate the feasibility of using such an approach for fast black-box modelization. The proposed regression models, characterized by a very limited computational demand, exhibit excellent performance over a large set of experimental data, with less than ten parameters but requiring a rather complex engine geometrical and operative description. On the other hand, the Neural Network model has been developed considering as independent variables only four measurable engine parameters and the training has been performed using a reduced set of experimental data. The results presented show a relevant precision improvement with respect the available models cited in literature. The different model structures developed are suitable for several uses, both for off-line and on-line applications.

INTRODUCTION

The evaluation of engine mechanical losses is a significant objective for engine designers due to its strong influence on engine life, fuel consumption and emission levels. Mechanical losses are responsible for crank shaft power decrease with respect to the indicated power generated by gas expansion in the engine cylinder. This work reduction is related with energy dissipation caused by both friction processes, generated by the relative motion of adjacent components within the engine (i.e. piston, rings, bearings, gears, pulleys, belts), and engine accessories driving (i.e. oil, water and power-steering pumps, generator, air conditioner).

Because of the complex phenomenology involved, mainly in the friction process, the building of engine mechanical efficiency model is not a trivial task. Nevertheless, the researchers have made a great effort for the development of comprehensive and accurate mechanical losses models and different model approaches have been proposed [1,2,3,4]. Among others, Mc Geehan [5] and Ciulli [6] presented a detailed description of friction phenomena between piston, rings and cylinder walls and an exhaustive analysis of available models has been found in the works of Ciulli [7] and Ciulli and Psarudakis [8]. Accurate studies have been performed by Rezeka and Henein [9] for the simulation of the instantaneous friction torque for a Diesel engine and by Patton et al. [10] on the global evaluation of friction mean effective pressure. Recent simulations have been carried out by Ciulli et al. [11] and Tuccillo et al. [12] for research NCG engine and Diesel engine, respectively. Furthermore, experimental analysis have been conducted by Koch et al. [13] for the evaluation of friction forces between piston, rings and cylinder walls as function of operating conditions for a SI engine. However, from the reviewed literature works emerges the limited availability of global engine mechanical efficiency models since all the followed approaches require a specific characterization on the particular engine.

The present work deals with the development of models for the evaluation of mechanical efficiency of a SI engine; these models are part of a set of sub-models with different approaches arranged in a hierarchical engine models structure [14,15]. This hierarchical structure [16] combines the use of both models and experimental data through an Experimental Design technique [17] to characterize the engine with a limited number of experimental data. These models are embedded in the code O.D.E.C.S. for the design of optimal engine control strategies for SI engines, currently used at Magneti Marelli. In this framework the required properties of mechanical efficiency model are: i) a reduced computational time, ii) a balanced precision with respect to other engine sub-models, iii) a limited experimental data set for the identification phase.

In the following sections the available literature models (Rezeka and Henein [9], Patton et al. [10]) are described and implemented for the current application. Two different approaches are then proposed: the first one relies on a fully black-box approach as function of engine operating variables, while the second one is derived from the more complex Rezeka and Henein [9] and Patton et al. [10] models suitably modified for their use in the framework of the present reasearch.

LITERATURE MODELS

In this section the two models proposed by Rezeka and Henein [9] and Patton et al. [10] are reviewed. They substantially differ for the time basis adopted for mechanical losses computation: in the former a crank angle basis is used, while a cycle average is performed for the latter model.

REZEKA-HENEIN MODEL

The model described in this paragraph allows estimating the instantaneous value of mechanical efficiency through the evaluation of dissipated torque in each engine mechanical subsystem as function of crank angle [9].

In the following, the Rezeka-Henein model equations are reported. The complete set of equations is split into two main groups describing the friction between piston and cylinder wall and the mechanical losses in the crankcase assembly system, respectively. For the computation, the indicated pressure signal and the knowledge of engine geometrical data are required. The total loss is then expressed as a friction torque by summing up each term.

The first group for the evaluation of the friction between piston and cylinder walls is composed of the following terms:

- Losses due to piston rings viscous lubrication (hydrodynamic):

$$\boldsymbol{T}_{f1} = \boldsymbol{a}_1 \cdot \Sigma \left\{ \left[\mu \cdot \boldsymbol{V}_{\boldsymbol{p,ist}} \left(\boldsymbol{P}_{\boldsymbol{eo}} + \boldsymbol{P}_{\boldsymbol{gas}} \right) \boldsymbol{w} \right]^{0.5} \boldsymbol{B} \cdot \left(\boldsymbol{n}_{po} + 0.4 \cdot \boldsymbol{n}_{pc} \right) \cdot \boldsymbol{r} \cdot |\boldsymbol{k}| \right\} \quad (1)$$

- Losses due to mixed lubrication regime (hydrodynamic and boundary) of piston rings near the top dead center:

$$\boldsymbol{T}_{f2} = \boldsymbol{a}_2 \cdot \Sigma \left\{ \pi \cdot \boldsymbol{B} \cdot \boldsymbol{n}_{\boldsymbol{pc}} \cdot \boldsymbol{w} \cdot \left(\boldsymbol{P}_{\boldsymbol{ec}} + \boldsymbol{P}_{\boldsymbol{gas}} \right) \Sigma \cdot \left(1 - |\boldsymbol{sin}\theta| \right) \cdot \boldsymbol{r} \cdot |\boldsymbol{k}| \right\} \quad (2)$$

- Losses due to piston skirt friction:

$$\boldsymbol{T}_{f3} = \boldsymbol{a}_3 \cdot \Sigma \left\{ \left(\frac{\mu \cdot \boldsymbol{V}_{\boldsymbol{p,ist}}}{\boldsymbol{h}} \right) \cdot \left(\boldsymbol{B} \cdot \boldsymbol{H}_{\boldsymbol{P}} \right) \cdot \boldsymbol{r} \cdot |\boldsymbol{k}| \right\} \quad (3)$$

The losses in the crankcase are computed considering the sources quoted below:

- Valve train friction:

$$\boldsymbol{T}_{f4} = \boldsymbol{a}_4 \cdot \left(\boldsymbol{n}_{\boldsymbol{v}} \cdot \boldsymbol{F}_{\boldsymbol{m}} \cdot \boldsymbol{r} \cdot \frac{|\boldsymbol{k}|}{\sqrt{\omega}} \right) \quad (4)$$

- Auxiliaries and unloaded bearing friction:

$$\boldsymbol{T}_{f5} = \boldsymbol{a}_5 \cdot (\mu \cdot \omega) \quad (5)$$

- Loaded bearing friction:

$$T_{f6} = a_6 \cdot \Sigma\left(\frac{\mu}{4} \cdot B^2 \cdot r_b \cdot P_{gas} \cdot \frac{|\cos\vartheta|}{\sqrt{\omega}}\right) \qquad (6)$$

In the equations (1, 2, 3 and 6) the summation is extended to all the engine cycle crank angles while the non-dimensional term k (eqs. 1, 2, 3 and 4) is:

$$k = \sin\vartheta + \frac{r}{l} \cdot \frac{\sin\vartheta \cdot \cos\vartheta}{\sqrt{\left\{1 - \left(\frac{r}{l}\right)^2 \cdot \sin\vartheta\right\}}} \qquad (7)$$

The coefficients $a_{1\text{-}6}$ in the equations (1 - 6) are proportional factors depending on the engine design and related with both geometrical data (i.e. rings shape, cylinder liner, piston inclination) and lubrication regime (i.e. oil film thickness).

PATTON-NITSCHKE-HEYWOOD MODEL

The model proposed by Patton, Nitschke and Heywood [10] predicts the friction mean effective pressure for a SI engine as function of geometrical and operating engine data. Three main groups are derived to account for friction, pumping and auxiliary losses from engine accessories, as shown below.

The friction losses are split into three part:

- Crankshaft bearing friction, due to boundary and hydrodynamic lubrication regimes and turbulent dissipation:

$$fmep_{1,1} \propto b_1 \frac{D_b}{B^2 \cdot S \cdot n_c} + b_2 \frac{N \cdot D_b^3 \cdot L_b \cdot n_b}{B^2 \cdot S \cdot n_c} + b_3 \frac{D_b^2 \cdot N^2 \cdot n_b}{n_c} \qquad (8)$$

- Reciprocating component group friction including piston, piston rings (both without gas pressure loading and considering the friction increase caused by gas pressure loading) and connecting rod friction:

$$fmep_{1,2} \propto b_4 \frac{V_p}{B} + b_5\left(1 + \frac{1000}{N}\right) \cdot \frac{1}{B^2} + b_6 \frac{P_{man}}{P_{amb}} \cdot \left[0.088 \cdot r_c + 0.182 \cdot r_c^{\left(1.33 - K'V_p\right)}\right] + b_7 \frac{N \cdot D_b^3 \cdot L_b \cdot n_b}{B^2 \cdot S \cdot n_c} \qquad (9)$$

- Valvetrain friction due to camshaft, cam follower and valve actuation mechanism:

$$fmep_{1,3} \propto b_8 + b_9 \frac{N \cdot n_b}{B^2 \cdot S \cdot n_c} + b_{10}\left(1 + \frac{1000}{N}\right)\frac{n_v}{S \cdot n_c} + b_{11} \frac{L_v^{1.5} \cdot N^{0.5} \cdot n_v}{B \cdot S \cdot n_c} + b_{12}\left(1 + \frac{1000}{N}\right) \cdot \frac{L_v \cdot n_v}{S \cdot n_c} \qquad (10)$$

The auxiliary component friction are predicted considering the sum of oil pump, water pump and non charging alternator friction, through the following equation:

$$fmep_2 \propto b_{13} N + b_{14} N^2 \qquad (11)$$

The pumping losses during intake and exhaust strokes are computed by the following equation:

$$fmep_3 \propto \left(P_{amb} - P_{man}\right) + \left(\frac{P_{man}}{P_{amb}} V_p\right)^2 + \frac{V_p^2}{n_v^2 \cdot r_{man}^4}\left(\frac{P_{man}}{P_{amb}}\right)^2 \cdot \left(\frac{1}{r_{man}^4} + \frac{1}{r_{exh}^4}\right) \qquad (12)$$

For the present application of the model the pumping losses term (eq. 12) is not considered since it has directly accounted from the indicated pressure cycle during both intake and exhaust strokes.

Consistently with the original Patton et al. [10] model formulation, all the geometrical data and the pressure terms in the equations (8 - 12) are expressed in millimeters and in kPa, respectively. The constant K' in the relationship (9) has been set to $2.38 \cdot 10^{-2}$ [s/m], as suggested by Patton et al. [10]. In the equations set (8-11) the coefficients $b_{1\text{-}14}$ must be identified making use of the available experimental data in order to characterize the particular engine system.

APPLICATION OF REZEKA-HENEIN AND PATTON-NITSCHKE-HEYWOOD MODELS

An application of the two models previously described [9, 10] has been carried out to check their prediction level on the engine used for the current research activity. The simulated values of mechanical efficiency obtained with the Rezeka and Henein and Patton et al. models have been compared with the corresponding steady-state experimental data after an appropriate identification of model coefficients ($a_{1\text{-}6}$, $b_{1\text{-}14}$) by means of regression techniques.

For the analysis of the cited models, a set of more than 400 experimental data have been used. It is worth to remark that the experimental data considered are part of an extended data set applied for the development and the identification of other engine models [14, 15] which are part of the mentioned hierarchical model structure [16]. These data were measured on a S.I. engine Fiat 2.0 liters 16 valves with a Magneti Marelli IAW4Q3.P8 E.C.U., at Istituto Motori-CNR laboratories in Naples. For each engine working condition, located in the Engine speed - Torque plane (Figure 1), 23 engine variables were measured by varying both A/F ratio from 11 to 18 and spark advance within knock and misfiring limits. For each of 426 steady-state mean pressure cycle an average of 288 consecutive pressure cycles, sampled by an AVL Indiskop system, was performed.

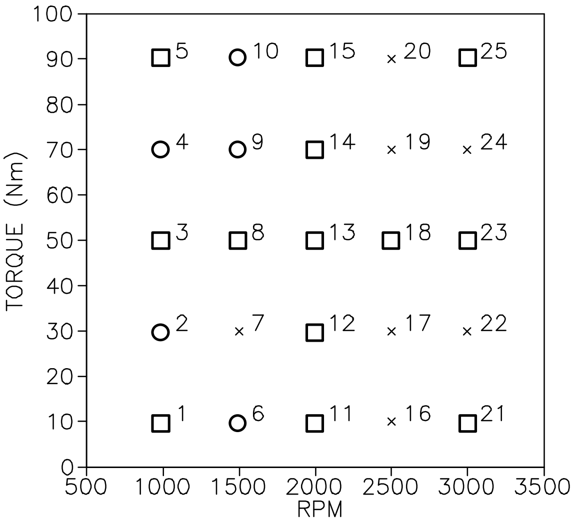

Figure 1 - Experimental grid plane (Engine speed - Torque).

Friction torque and friction mean effective pressure, which are not easily available as direct measures on the engine, have been computed through pressure cycle and measured engine variables. Mechanical efficiency has been computed as ratio between brake power measured on the dynamometer and the indicated power computed through the mean indicated pressure:

$$\eta_m = \frac{P_e}{P_i} \tag{13}$$

Experimental friction power is then given by the following relationship:

$$T_{f,meas} = \frac{P_i \cdot (1-\eta_m)}{\omega} \tag{14}$$

Experimental mean effective friction pressure is computed as difference between mean indicated pressure and mean effective pressure:

$$fmep_{meas} = (imep - bmep) \tag{15}$$

where all the terms are expressed in kPa, consistently with Patton et al. model [10].

The model identification has been conducted making use of a multiple linear regression analysis with the commercial code Statistica [18, 19]. The model coefficients have been found via least square technique on the whole data set composed of 426 experimental points. In what follows the results of the identification analysis are discussed.

In the Figure 2 the comparison between the observed and the computed with Rezeka and Henein model [9] (see eqs. 1-6) friction torque (14) is shown. From the analysis of the figure the poor accuracy achieved is evident, confirmed also by the quite unsatisfactory value of correlation index (R^2=0.58). Moreover, a residual analysis has been performed and shown through the distribution histogram of Figure 3, where only the 60% of simulated data present an error in the interval (-2, +2 [Nm]).

The comparison between observed and computed, with the model of Patton et al. [10], friction mean effective pressure is presented in the Figure 4, which reveals the same level of accuracy found with the previous model. Furthermore, the correlation index R^2 attains a value of 0.57 while, from the residual analysis (see Figure 5), only the 51% of the data falls in the accuracy limits of (-10, +10 [kPa]).

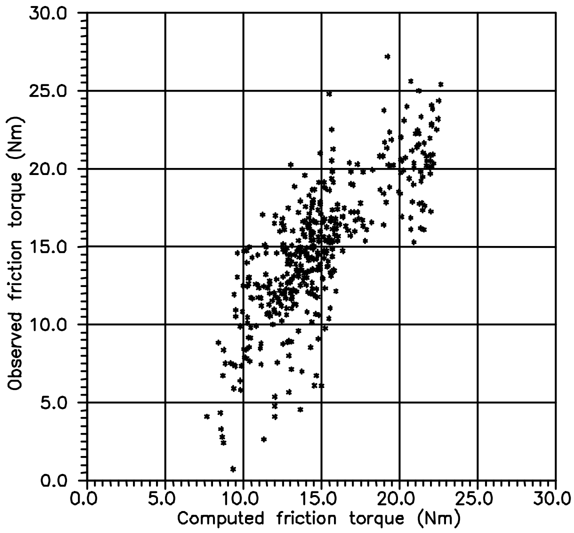

Figure 2 - Comparison between observed and computed friction torque - Rezeka and Henein model.

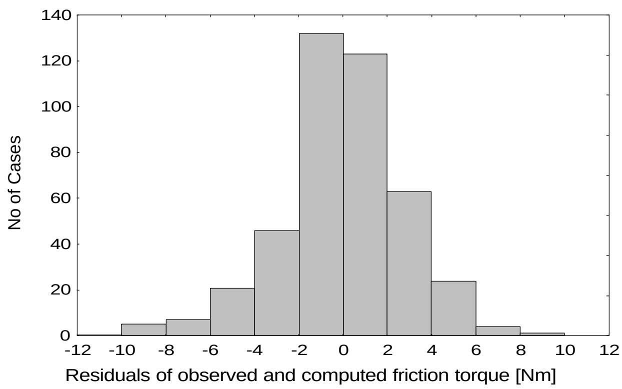

Figure 3 - Distribution of residuals - Rezeka and Henein model.

The results show the inadequate precision level reached by applying the two models to the engine used for the current research. Concerning the first model (Rezeka and Henein [9]), it should be pointed out that it was originally developed for a Diesel engine, which presents higher inertia levels and lower engine speed regimes with respect to SI engines. Moreover, in the relationship (4) and (6) the mean angular speed has been considered instead of the instantaneous one as suggested by the authors [9]. On the other hand, although the model of Patton et al. [10] was developed for SI engine its mean value formulation is intrinsically less accurate. The analysis performed show that these models could not be applied through a straightforward implementation for any engine configuration. Indeed, the limited level of built-in physical information is inadequate to describe the complex phenomena involved in both friction and lubrication processes taking place in an engine.

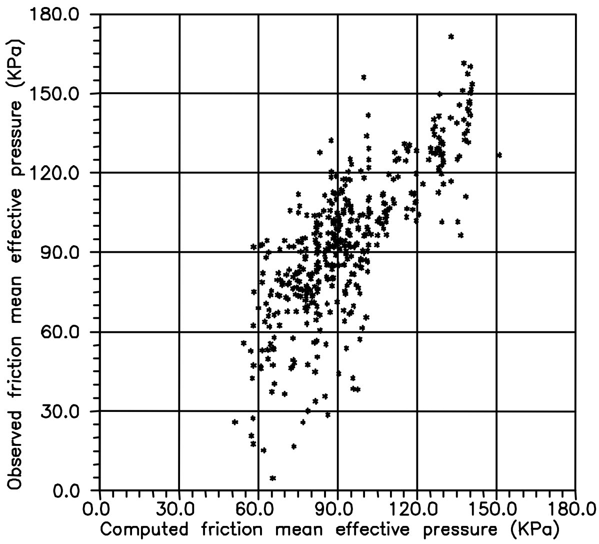

Figure 4 - Comparison between observed and computed friction mean effective pressure - Patton, Nitschke, Heywood model.

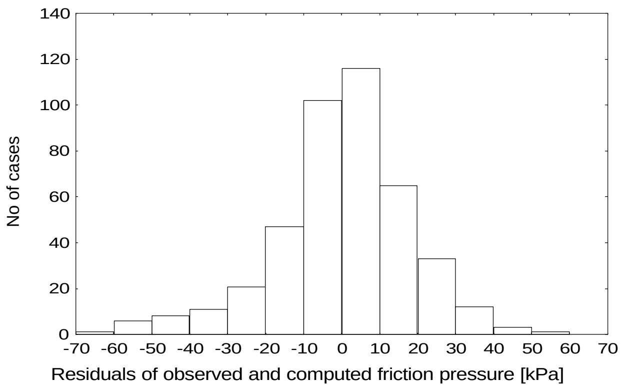

Figure 5 - Distribution of residuals - Patton, Nitschke, Heywood model.

It is worth to remember that the model performance has been originally tested on a limited set of experimental data [9,10]. Nevertheless, a lack of model applications referred to an extended set of experimental data, as the one used in the present work, has been found in the literature.

DEVELOPMENT OF ALTERNATIVE MODELS FOR MECHANICAL EFFICIENCY ESTIMATION

The results shown above led to the opportunity to develop a set of mechanical efficiency models starting from the reference model structures [9,10]. For the current research purposes, two main approaches have been followed. The former model has been designed as a fast black-box input-output model, while the latter has been substantially derived from Rezeka and Henein [9] and Patton et al. [10] models, including the influence exerted by further engine variables and pressure cycle measurements.

The main goal of the present research activity is the development of a model for mechanical efficiency estimation, to be integrated in a more extended model structure for the design of engine control strategies, rather than an accurate study of mechanical losses sources. Therefore, the model is requested to be easily validated on the engine currently used and to offer good precision level and limited computational resources in accordance with control purposes applications. In order to meet these features an extended set of experimental data has to be measured by the use of conventional laboratory tools, leading to deal with some experimental troubles, which are mentioned below:

- The pressure cycle sampling system presents poor resolution during the intake and exhaust strokes, where the pressure values are lower.
- Pressure cycles measured in low load operating conditions are generally affected by a great cyclic dispersion, leading to an excessive variability of the sampled signal. This problem can be overcome increasing the number of data sampled for the mean pressure cycle evaluation.
- As a consequence, some particularly high values of mechanical efficiency, close to unit, can result in some conditions (fig. 6, 9, 11, 13). These values, which are obviously unrealistic, have not been filtered since their elimination would have distorted the statistical distribution of the errors and therefore would have led to underestimation of the mechanical efficiency itself.
- The top dead center signal is affected by uncertainty due to the kinematics train action. A sensitivity analysis has then been carried out simulating crank angle position variations of $\pm$ 1 degree; it has been found that this uncertainty does not affect substantially the subsequent modeling and validation phases.

FAST BLACK BOX MODELS

The development of this class of models does not require an accurate description of the physical phenomena responsible for friction losses (lubrication regimes, oil film thickness, and gas pressure loading on piston rings). It allows reducing substantially the computational time and reaching a precision level compatible with the sub-models included in the code O.D.E.C.S. [14]. In the following sections two models structures selected for fast black-box applications are reported. The former relies on classical multiple non-linear regressions the latter is based on a neural network.

Multiple non-linear regression

A multiple non-linear regression has been applied for model structure definition, paying particular attention to statistical significance of model parameters. The influence exerted by each engine variable over the experimental data set has been accurately analyzed by using the *p-level* index. A *p-level* index equal to 0.05 states that the current variable and the process to be described are not correlated with a probability of 5%, so that a correlation analysis can be usually considered positive if *p-level* values less than 5% are reached [19, 20, 21].

The following relationship describes the mechanical efficiency estimation model:

$$
\begin{aligned}
h_{\boldsymbol{m}} = {} & \boldsymbol{a}_0 + \boldsymbol{a}_1 \cdot \left(\frac{\boldsymbol{N} \cdot \boldsymbol{T}}{10^3}\right) + \boldsymbol{a}_2 \cdot \left(\frac{\boldsymbol{T}}{10^2}\right)^2 + \\
& \boldsymbol{a}_3 \cdot \left[\left(\frac{\boldsymbol{N}}{10^3}\right)^2 \cdot \left(\frac{\boldsymbol{P}_{\boldsymbol{man}}}{10^4}\right)^2\right]^{0.2365} + \boldsymbol{a}_4 \cdot \left(\frac{10^3}{\boldsymbol{N}}\right) + \\
& \boldsymbol{a}_5 \cdot \left[\left(\frac{\boldsymbol{N}}{10^3}\right) \cdot \left(\frac{\boldsymbol{T}}{10^2}\right)^2\right]^{-6.89 \cdot 10^{-3}} + \\
& \boldsymbol{a}_6 \cdot \left(\boldsymbol{T}_{\boldsymbol{man}}\right) + \boldsymbol{a}_7 \cdot \left(\boldsymbol{P}_{\boldsymbol{man}}\right)^{0.3304} + \boldsymbol{a}_8 \cdot \left(\dot{\boldsymbol{m}}_{\boldsymbol{air}}\right)
\end{aligned}
\qquad (16)
$$

Where the model parameters $\boldsymbol{a}_i$ have been evaluated by means of a multiple linear regression technique while the fraction exponents in eq. 16 have been computed by means of non-linear regression techniques. Model prediction levels have been tested by a comparison between simulated and measured mechanical efficiency over 426 engine operating steady-state conditions.

The results obtained by applying the multiple regression approach can be considered satisfactory, as confirmed by the reached values of the *p-level* indices (less than 0.001) reported in Table I together with the computed regression coefficients $\boldsymbol{a}_i$ and the correlation index $\boldsymbol{R}^2$.

Table I – *p-level* indices, correlation index and regression coefficients computed for eq. 16.

	a_0	a_1	a_2	a_3	a_4
Estimated	10.82402	.00173	-.3859	-.5217	-.5410
p-level	.0	.0	.0	.0	.0

	a_5	a_6	a_7	a_8	R^2
Estimated	-10.8629	.001439	.06819	.00231	.9606
p-level	.0	.000302	.0	3.0 e-6	

In the Figure 6 the good estimation levels reached by the non-linear multiple regression approach is shown by comparing measured and computed mechanical efficiency. The lack of data in the range [0.55÷0.63] is due to an incomplete coverage of experimental grid (Figure 1). From residual statistical analysis reported in Figure 7, 55 % of data falls inside the range [-0.02÷0.02] while only the 9 % is off the range [-0.06÷0.06].

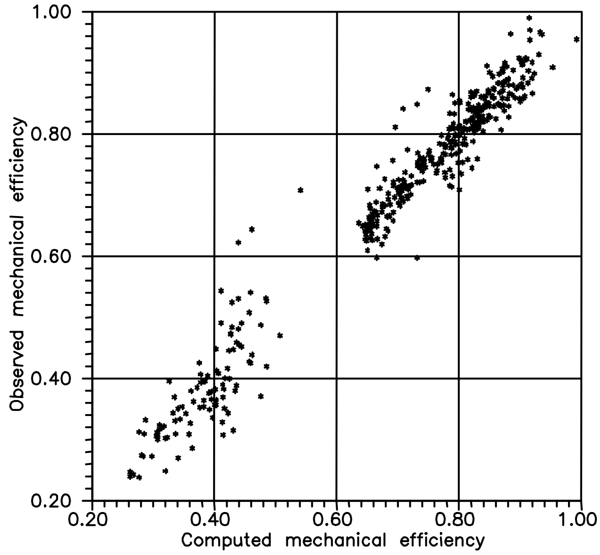

Figure 6 – Comparison between measured and estimated mechanical efficiency – Multiple non-linear Regression (eq. 16).

From the analysis of both model structure and obtained results, some considerations on model accuracy, flexibility and applicability arise. Regarding to model precision, the achieved accuracy is satisfactory but not excellent with respect to the complex procedure required for model parameter evaluation. Furthermore, the presence of measured brake torque *T* in the relationship (16), which in turn is a computed variable in an engine performance evaluation model, could lead to a not straightforward model application. Indeed, an iterative procedure should be applied in order to compute contemporarily, through distinct model, both mechanical efficiency and brake torque. Thus resulting in a global model precision reduction and in a computational time increase. Nevertheless, other analysis were carried out to replace the brake torque with other engine variables. From these tests a relatively poor model precision has been reached compared with the resulting model structure complexity. Many of these problems have been overcome by the use of Neural Network approach, which allowed a more direct definition of model parameters and to straightforward model application.

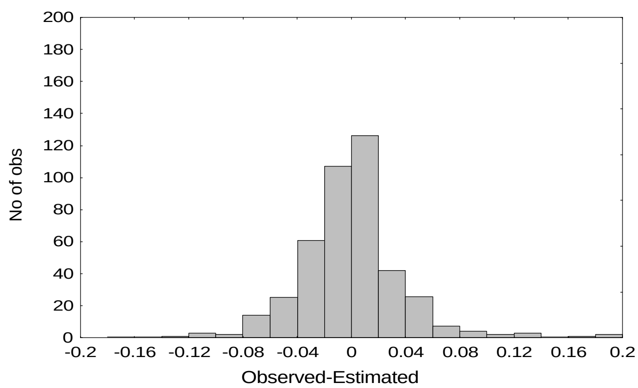

Figure 7 – Residuals of observed and estimated mechanical efficiency – Multiple non-linear Regression (eq. 16).

Neural network

In the present section the artificial neural network model application is discussed. A complete description on basic theory, capabilities and procedures is beyond the scope of the present paper and the reader is addressed to the selected bibliography [22,23,24]. Some recent neural network applications have been presented in literature showing its favorable use for engine modeling purposes [25,26,27,28,29].

An Artificial Neural Network is composed of several elementary interconnected processing elements working in a parallel way, the perceptrons. From the analogy with human brain behavior, Artificial Neural Networks are able to reproduce a process from training examples (neurocomputing approach [23]) rather than from a coded algorithm which simulate the process on the basis of a mathematical model (programmed computing approach [23]). Due to the use of experience knowledge, Neural Networks have relevant capabilities in term of generalization from limited training data sets making them able to work outside the training domain (i.e. extrapolation). Moreover, other neural network capabilities refer to their robustness in presence of noisy input data because the stored knowledge is spread over the entire perceptron structure instead of being concentrated in few units [22].

For the purpose of the present application a multi-layer feedforward neural network has been chosen to model the engine mechanical efficiency as function of engine control and state variables (engine speed, manifold pressure, air-fuel ratio, spark advance). The choice of this set of independent variables, together with a proper neural network structure, is well suited to model the mechanical efficiency in a black-box manner. The prediction level obtained by following this approach is comparable with the one reached through the multiple-non linear regression which makes use of the brake torque as independent variable.

The selected neural network structure is composed of three layers with one input, one hidden and one output layers. The input layer has four neurons one for each independent variable, the hidden layer has nine units, while the output layer presents one neuron. The signals propagating from the input to the output layers are processed by the neurons by means of biased bipolar continuous activation functions. Each neuron is linked with the previous layer neurons through a weighted connection whose level is found making use of a training procedure. Such structure configuration presents the minimum number of layers and neurons compatible with the process to be represented. This choice has been performed to reduce the effect of neural network overparametrization[1]. For the training process the well established backpropagation error algorithm has been used to found both weight and function biases [22,23, 29]. In the Figure 8 a generic multi layer neural network structure is shown.

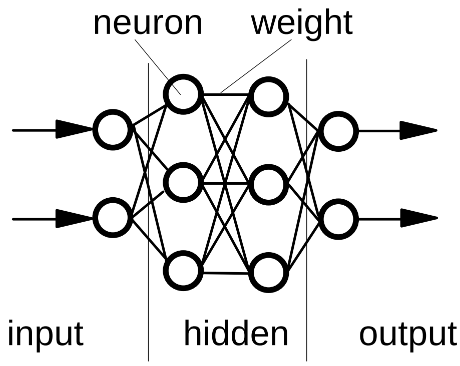

Figure 8 - Generic Multi Layer Neural Network Structure.

To train the network a set of "examples" is considered, for each training the desired output of the network being known (i.e. experimental data). At every iteration the error between the experimental data and the corresponding estimated value is propagated backward from the output layer to the input one through the hidden layers. During the backpropagation both weights and biases are tuned as function of the error gradient through the learning rate. The weights updating is also controlled by a momentum constant term. The learning rate and the momentum terms allow to speed up and to stabilize the minimum error search process [22,23,29].

For the purpose of the present work the training set has been chosen selecting the most meaningful experimental data, indicated with square symbols in the torque-engine speed grid (Figure 1). Furthermore, for each operating condition, combinations of three air-fuel ratio values and three spark advance angles have been selected, finally obtaining a set of 117 training experimental data. The remaining 309 experimental data have then been used to test the neural network prediction level.

In Figure 9 a comparison between observed and computed mechanical efficiency is shown. The prediction level can be considered satisfactory, as confirmed from residual histogram reported in Figure 10. From the statistic analysis a 49 % of data falls inside the residual range [-0.02÷0.02] while only 13 % is off the range [-0.06÷0.06] and the correlation index is R^2=0.934.

From the results obtained by applying the neural network model, some interesting features of such approach come to light. The first aspect to be pointed out is the precision level reached with a limited number of experimental data required for the training process, in comparison with the previous multiple regression model. Furthermore, by considering other appropriate independent variables the accuracy could be enhanced, particularly in the low mechanical efficiency region [0.2 ÷ 0.4]. Indeed, in this region the predicted data (see Figure 9) present a larger spread with respect to the higher mechanical efficiency

[1] When a large neural network structure is considered a high training accuracy is reached, while a loss of precision on the data not belonging to the training examples could occur.

area. A preliminary test has been conducted taking into account the influence of the manifold temperature, already included in the multiple regression (16), with a negligible precision enhancement. Further investigations are under course in order to find the proper combination of even correlated independent variables (i.e. air mass flow, ambient pressure and temperature, water and oil temperature) which can improve the prediction level.

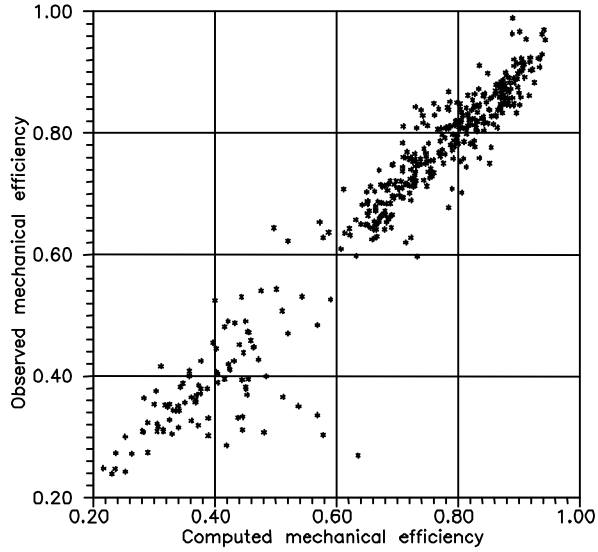

Figure 9 - Comparison between observed and simulated mechanical efficiency - Neural Network

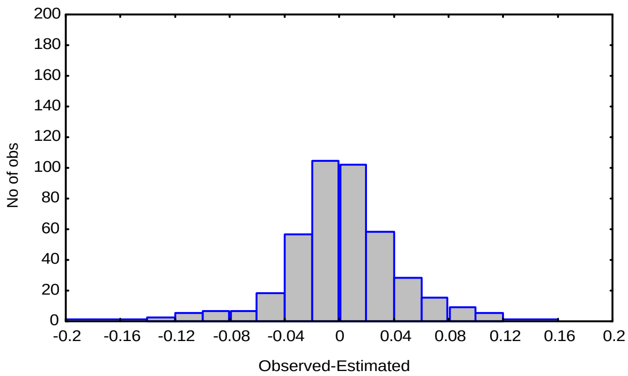

Figure 10 - Residuals of observed and estimated mechanical efficiency - Neural Network.

PRESSURE CYCLE BASED MODEL

A more complex model structure has been designed starting from Rezeka and Henein [9] and Patton et al. [10] models, by including the effects of other engine variables. Furthermore, the friction torque in equations 1 to 6 and the friction mean effective pressure in equations 8 to 11 are normalized with respect to the brake torque and the mean indicated pressure, respectively.

A multiple linear regression technique in forward stepwise mode has been used to determine the regression model functional form, allowing to select the most meaningful engine variables among the whole experimental data set. The significance level has been evaluated by means of statistical analyses on partial correlation indices, taking into account the mutual relationships between the variables. Two formulations have been obtained modifying two regression control parameters, such as the tolerance and the *F to enter* term, which indicate the threshold for the functional correlation between any independent variable and the process to be described. The tolerance represents the complement to one of the square correlation index between the current variable and all the other independent variables. The *F to enter* term is a significance level index related to the introduction of the current variable in the regression structure and is computed as ratio between the regression mean squares and residual mean squares. A decrease in the tolerance lead to a greater number of variables to be included in the regression; nevertheless, the selection of a too low tolerance value could lead to an over-parametrized structure. Analogously, an increase in the *F term* cause a greater threshold level to be reached by the significance level of each variable to be included in the regression model, thus resulting in a reduced number of independent variables to be considered. Finally, a tolerance reduction and an *F term* increase lead to functional structures with a greater number of variables and higher precision level.

For the current analysis thirty independent variables have been selected, also considering some terms obtained as combination of engine variables included in Rezeka and Henein [9] and Patton et al. [10] models.

The functional structure for mechanical efficiency estimation has been finally expressed by the following relationship, with tolerance and *F term* set respectively to 0.01 and 1.0:

$$
\begin{aligned}
\eta_m = {} & a_0 + a_1 \cdot \frac{1}{T} \cdot \\
& \sum \left\{ \pi \cdot B \cdot n_{pc} \cdot w \cdot \left(P_{ec} + P_{gas} \right) \cdot \left(1 - \left| \sin \vartheta \right| \right) \cdot r \cdot |k| \right\} + \\
& a_2 \cdot \frac{1}{T} \cdot \sum \left\{ \left(\frac{\mu \cdot V_{p,ist}}{h} \right) \cdot \left(B \cdot H_P \right) \cdot r \cdot |k| \right\} + \\
& a_3 \cdot P_{man} + a_4 \cdot Log(T) + \\
& a_5 \cdot \frac{P_{man}}{P_{amb} \cdot imep} \cdot \left[0.088 \cdot r_c + 0.182 \cdot r_c^{\left(1.33 - K' \cdot V_p\right)} \right] + \\
& a_6 \cdot Log(P_{man})
\end{aligned}
\tag{17}
$$

where the presence of only seven parameters to be identified is remarked. The summation terms are referred to the crank angle domain, extended over the engine cycle. The first two terms represent friction losses due to piston rings and piston skirt respectively, and have been derived from Rezeka and Henein [9] model, while the fifth term is referred to the friction losses due to gas pressure loading on piston rings, described in Patton et al. [10] model.

In order to improve model prediction level, several tests have been carried out by a suitable tuning of the control parameters (tolerance and *F term*). The best results have been found setting the tolerance to 0.001 and the *F term* to 9.0:

$$\begin{aligned} \eta_m = {} & a_0 + a_1 \cdot \frac{1}{T} \cdot \\ & \Sigma\left\{\pi \cdot B \cdot n_{pc} \cdot w \cdot \left(P_{ec} + P_{gas}\right)\cdot\left(1-|\sin\vartheta|\right)\cdot r\cdot|k|\right\} + \\ & a_2 \cdot \frac{1}{T}\cdot\Sigma\left\{\left(\frac{\mu \cdot V_{p,ist}}{h}\right)\cdot\left(B\cdot H_P\right)\cdot r\cdot|k|\right\} + \\ & a_3 \cdot P_{man} + a_4\cdot Log(T) + \\ & a_5 \cdot \frac{P_{man}}{P_{amb}\cdot imep}\cdot\left[0.088\cdot r_c + 0.182\cdot r_c^{\left(1.33-K'\cdot V_p\right)}\right] + \\ & a_6\cdot Log(P_{man}) + \\ & a_7\cdot\left[\left(\frac{P_{amb}}{10^4}\right)\cdot\left(\frac{T}{10^2}\right)\right] + a_8\cdot\left(\frac{N}{10^3}\right)^2 + a_9\cdot\left(\dot m_{air}\right) \end{aligned} \qquad (18)$$

where three new variables have been introduced, thus resulting in ten parameters to be identified. A least square technique has been applied to compute the regression coefficients a_i in both the equations (17, 18) over the entire set of 426 experimental data.

In table II regression coefficients and *p-level* corresponding to the first model (17) are reported with the correlation index which attains the remarkable value of 0.9821. The satisfactory level is also evident in Figure 11 where the comparison between observed and measured mechanical efficiency is shown and in Figure 12 where the residual distribution is reported. From residuals analysis it emerges that 66 % of data is inside the range [-0.02÷0.02], while only 8 % is off the range [-0.06÷0.06].

table II - regression coefficients (17), p-level and correlation index.

	a_0	A_1	a_2	a_3
Estimated	3.46201	-0.2455	0.0253	2.0 e-6
p-level	.0	.0	.0	6.2 e-5

	a_4	A_5	a_6	R^2
Estimated	0.8363	0.05632	-0.9251	0.9821
p-level	.0	.0	.0	

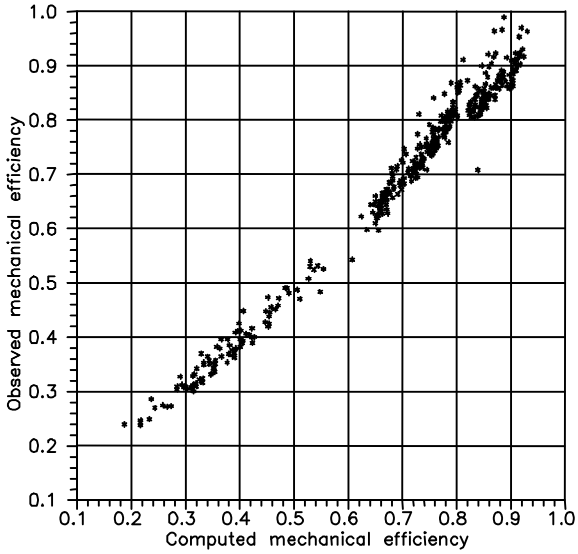

Figure 11 - Comparison between observed and computed mechanical efficiency - eq. (17).

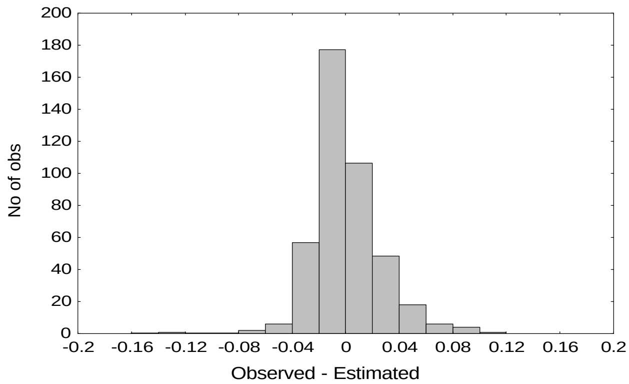

Figure 12 - Residuals of observed and estimated mechanical efficiency - eq. (17).

Excellent results have also been obtained by applying the second model (18) which led to an even better correlation index (0.988). In table III regression coefficients, *p-level* and correlation index are reported, while in Figure 13 and 14 the comparison between measured and estimated mechanical efficiency and the residual distribution are shown respectively.

table III - regression coefficients (18), p-level and correlation index.

	A_0	a_1	a_2	a_3	a_4	a_5
Estim.	6.977	-.0151	.0418	1.0 e-5	1.093	.0558
p-level	.0	.0	.0	.0	.0	.0

	A_6	a_7	a_8	a_9	R^2	
Estim.	-1.842	-.0346	-.0135	.0012	.988	
p-level	.0	.00030	.0	3.0 e-6		

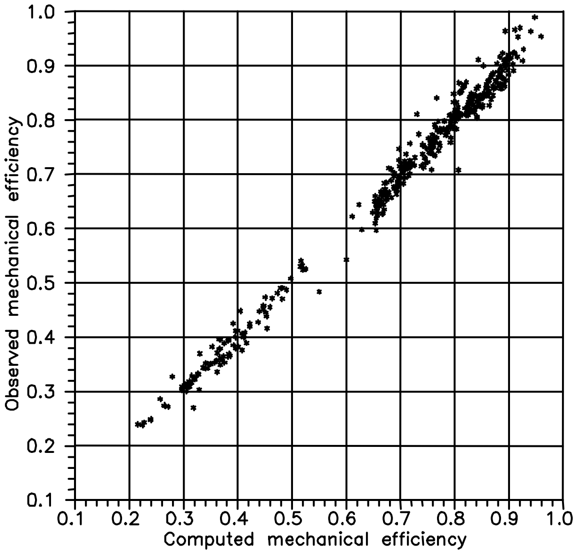

Figure 13 - Comparison between observed and computed mechanical efficiency - eq. (18).

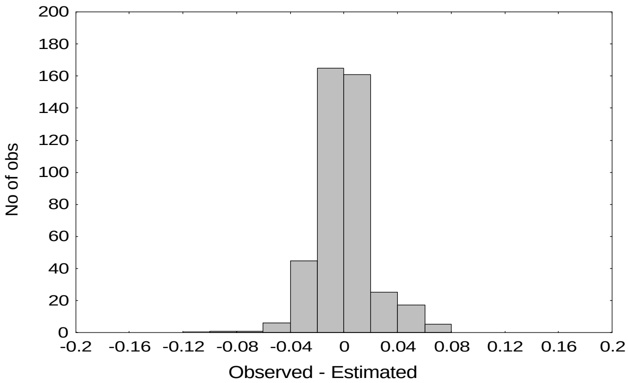

Figure 14 - Residuals of observed and estimated mechanical efficiency - eq. (18).

The presented results show the high accuracy achieved with the proposed pressure cycle models (eqs. 17,18) which require the identification of seven and ten regression parameters, respectively. Thus, a reduced number of suitably selected experimental data is required for model identification.

A valuable aspect of the presented modeling activity, both black-box and pressure cycle based, is related with the large set of experimental data used for development, also considering critical engine working conditions such as low regimes at high load, lean mixture and reduced spark advance operations.

CONCLUSION

A set of SI mechanical efficiency models to be implemented in general models oriented to engine control have been developed and validated on a wide experimental data set. More than 400 operating conditions have been investigated building a complete data set, including in-cylinder pressure cycles.

The first part of the work has concerned with the application of the available model in the literature. The models of Rezeka and Henein [9] and Patton et al. [10] have been applied and an identification analysis has been conducted to find the unknown model parameters. The precision achieved with these models is far from the accuracy levels required. Two other approaches have been followed, the former has led to the development of fully black-box models for fast computation applications (i.e. optimization), while the other one requiring the pressure cycle data can be used for accurate engine performance evaluation.

For black box models a regression based model has been built considering global engine working variables (manifold pressure, brake torque, air flow rate, engine speed). Then a Multi Layer Neural Network has been also used considering only easy-to-measure engine variables (engine speed, manifold pressure, air-fuel ratio, spark advance). The precision achieved is comparable for both model but the latter one seems the most promising because of its straightforward parameters specification.

The second model approach is based on the combined use of both operating and pressure cycle data. Its structure and unknown coefficients are found by using a multiple stepwise linear regression procedure. In this case the accuracy obtained fulfills the requirements of applicability in the framework of phenomenological engine models.

As general remark, it could be concluded that the models previously proposed in literature and examined in this work are not enough general to be successfully applied to engines whose structure differs from the one where the models were originally developed. It also emerges that a more detailed physical description of the complex phenomena related to friction is needed to enhance their predictive capabilities.

On the other hand, further work is under course in order to asses the direct applicability of the developed models to other engine structures and to define the minimum set of experimental point to be investigated (i.e. most significant operating conditions). This latter goal will be pursued through the combined use of both Neural Network and Experimental Design Techniques [17].

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CONTACT

Ivan Arsie, Cesare Pianese, Gianfranco Rizzo

Department of Mechanical Engineering, University of Salerno, 84084 Fisciano (SA), Italy

Ph./Fax +39 89 964069

E-mail:grizzo@unisa.it

URL: http://tecno.diiie.unisa.it/dimec/macchine

Roberto Flora, Gabriele Serra

Magneti Marelli, Engine Control Division, Via del Timavo 33, 40134 Bologna, Italy

E-mail:gserra@bologna.marelli.it

REFERENCES

[1] Ferguson C.R. (1986) - **Internal Combustion Engine**, Applied Termosciences, John Wiley.

[2] Heywood J.B. (1988) - Internal Combustion Engine Fundamentals, MC Graw Hill.

[3] Ramos J.I. (1989) - **Internal Combustion Engine Modeling**, Hemisphere Pubblishing Corporation.

[4] Ferrari G. (1992) - **Motori a Combustione Interna**, Il Capitello.

[5] Mc Geehan J.A. (1978) - A Literature Review of the Effects of Piston and Ring Friction and Lubricating Oil Viscosity on Fuel Economy, SAE paper 780673, pp.2619-2638.

[6] Ciulli E. (1991), A Review of Internal Combustion Engine Losses. Part 1: Specific Studies on the Motion of Piston, Valves and Bearings, IMechE 1992, Proc. Instn. Mech. Engrs., Vol. 206, pp.223-236.

[7] Ciulli E. (1991), A Review of Internal Combustion Engine Losses. Part 2: Studies for Global Evaluations, IMechE 1992, Proc. Instn. Mech. Engrs., Vol. 207, pp.229-240.

[8] Ciulli E., Psarudakis P.(1991), Sulla Valutazione Teorica e Sperimentale delle Perdite Meccaniche nei Motori a Combustione Interna, 46° Congresso Nazionale dell'Associazione Termotecnica Italiana-ATI Cassino-Gaeta, 25-27, settembre 1991. (in Italian)

[9] Rezeka S.F., Henein N.A. (1984) - A New Approach to Evaluate Instantaneous Friction and Its Components in Internal Combustion Engines, SAE paper 840179, pp.1.932-1.943.

[10] Patton K.J., Nitschke R.G., Heywood J.K. (1989) - Development and Evaluation of a Friction Model for Spark-Ignition Engines SAE paper 890836, pp.1441-1461.

[11] Ciulli E., Rizzoni G., Dawson J. (1996) Numerical and Experimental Study of Friction on a Single Cylinder CFR Engine, SAE paper 960357, pp.181-188.

[12] Tuccillo R., Arnone L., Bozza F., Nocera R., Senatore A. (1993) - Experimental Correlations for Heat Release and Mechanical Losses in Turbocharged Diesel Engines, SAE paper 932459, SAE Off-Highway International Congress & Exposition, Milwaukee, Wisconsin, settembre 1993, SAE Transactions Vol. 102 - Journal of Engines - section 3, pp. 2073-2086, 1994.

[13] Koch F., Geiger U., Hermesen F.G. (1996) - Piffo-Piston Friction Force Measurements During Engine Operation SAE paper 960306, pp.151-157.

[14] Arsie I., De Franceschi F., Pianese C., Rizzo G. (1996) - O.D.E.C.S. - A Computer Code for the Optimal Design of S.I. Engine Control Strategies, SAE Paper 960359, International Congress & Exposition, Detroit Michigan, February 26-29 1996, SP-1169, pp. 195-208.

[15] Arsie I., Pianese C., Rizzo G. (1997) - Identification of Emission Models in a Spark Ignition Engine for Control Applications, 5th IEEE Mediterranean Conference on Control and Systems, Paphos - Cipro, July 21-23 1997.

[16] Arsie I., Gambino M., Pianese C., Rizzo G. (1996) - Development and Validation of Hierarchical Models for the Design of Engine Control Strategies, Meccanica, Kluwer Academic Publisher, N° 5 V. 32 pp. 397-408.

[17] Pianese C., Rizzo G. (1996) - Interactive Optimization of Internal Combustion Engine Tests by Means of Sequential Experimental Design, "3rd Biennial European Joint Conference on Engineering Systems Design and Analysis - ESDA 96", Petroleum Division of ASME, Montpellier, France, July 1-4,1996, PD-vol. 80, pp. 57-64.

[18] Statistica for Windows (1994) - Users Manual, StatSoft, Inc, Tulsa OK (USA).

[19] Accarino S. (1997) - Sviluppo e Validazione Sperimentale di Modelli per il Calcolo del Rendimento Meccanico di un Motore Automobilistico, Mechanical Engineering Degree Thesis, University of Salerno.

[20] Draper N.R., Smith H. (1981) **Applied Regression Analysis**, John Wiley & Sons.

[21] Moore D.S., Mc Cabe G.P. (1989**), Introduction to the Practice of Statistics**, W.H. Freeman and Company.

[22] Patterson D.W. (1995), **Artificial Neural Networks - Theroy and Applications**, Prentice Hall.

[23] Hecht-Nielsen R. (1987), **Neurocomputing**, Addison-Wesley.

[24] Kolmogorov A. N. (1957), On the Representation of Continuous Functions of Many Variables by Superposition of Continuous Functions of One Variable and Addition, Amer. Math. Society Translations, 28, pp. 55-59, 1965, traduzione dall'originale in russo apparso su Dokl. Akad. Nauk. SSSR, 108, 1957, pp. 179-182.

[25] Shayler P.J., Goodman M.S., Ma T. (1996), Transient Air/Fuel Ratio Control of an S.I. Engine Using Neural Networks, SAE Paper n. 960326.

[26] Ortmann S., Glesner M., Rychetsky M., Tubetti P., Morra G. (1998), Engine Knock Estimation Using Neural Networks based on a Real-World Database, SAE Paper n. 980513, SP-1357, pp. 17-31.

[27] Ayeb M., Lichetenthäler D., Winsel T., Theuerkauf H.J. (1998), SI Engine Modeling Using Neural Network, SAE Paper n. 980790, - SP-1357 pp. 107-115.

[28] Holzmann H., Halfmann Ch., Isermann R. (1998), Neuro-Fuzzy Modeling of Automotive SI-Engine Characteristics, in proc. of IFAC Symposium Advances in Automotive Control 98, Mohican State Park, Loudonville, OH, USA, February 26 - March 1, 1998, pp. 156-160.

[29] Arsie I., Pianese C., Rizzo G. (1998), Enhancement of Control Oriented Engine Models Using Neural Network, 6th IEEE Med. Conf., Alghero, Italy, July 9-11 1998.

DEFINITIONS, ACRONYMS, ABBREVIATIONS

a_i [/] i-th regression coefficient;

A/F [/] Air-Fuel ratio;

B [m] Cylinder bore;

bmep [kPa] Brake mean effective pressure;

D_b [m] Bearing diameter;

F_m [N] Springs load;

fmep [kPa]Friction mean effective pressure;

h [m] Oil film thickness;

H_p [m] Piston skirt length;

l [m] Connecting rod length;

imep [Pa] Indicated mean effective pressure;

L_b [m] Bearing thickness;

L_i [J] Indicated work per cycle;

L_v [m] Max valve lift;

$\dot{m}_{air}$ [kg/h] Intake air flow;

M_e [Nm] Engine torque;

N [rpm] Engine speed;

n_b [/] Number of main bearings;

n_c [/] Number of cylinders;

n_{pc} [/] Number of rings;

n_{po} [/] Number of oil rings;

n_v [/] Number of valves per cylinder;

P_e [W] Brake power;

P_{ec} [Pa] Ring pressure loading;

P_{eo} [Pa] Oil ring pressure loading;

P_f [W] Friction Power;

P_{gas} [Pa] In-Cylinder gas pressure;

P_i [W] Indicated power;

P_{man} [Pa] Intake manifold pressure;

P_{max} [Pa] Max in-cylinder gas pressure;

pmep [kPa] Pumping mean effective pressure;

r [m] Crank radius;

R^2 [/] Correlation index;

r_b [m] Bearings radius;

r_c [/] Compression ratio;

r_{exh} [/] Exhaust valve diameter / cylinder bore Ratio;

r_{man} [/] Intake valve diameter / cylinder bore Ratio;

S [m] Piston stroke;

T [Nm] Brake torque;

T_f [Nm] Friction torque;

T_{man} [°C] Intake air temperature;

T_w [°C] Cylinder wall temperature;

V [m^3] Current piston volume;

V_p [m/s] Mean piston speed;

$V_{p,ist}$ [m/s] Current piston speed;

w [m] Piston ring thickness;

Greek symbols

α [/] Air-fuel ratio;

β [°]Throttle opening;

η_m [/] Mechanical efficiency;

μ [Kg/ms] Dynamic viscosity;

θ [°] Crank angle;

ρ [kg/m^3] Density;

τ_{inj} [ms] Injection time;

ω [rad/s] Angular speed;

Subscripts

Air Air;

amb Ambient;

exh Exhaust;

man Manifold;

meas Measured;

pred Predicted;

w,wall Cylinder wall.