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Determination of the maximum compression pressure of a spark-ignition engine based on a recurrent artificial neural network

Determinación de la presión máxima de compresión de un motor de encendido provocado basado en una red neuronal artificial recurrente

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Abstract

This research presents an explanation of the applied methodology for the determination of the maximum compression pressure of a reciprocating internal combustion spark-ignition engine (SIE), which is based on a study that begins with the characterization of amper-age consumption curves of the starter motor. A proto-col for data acquisition and subsequent statistical anal-ysis is applied. The statistical values of the signal as energy, average, standard deviation, variance, kurtosis, asymmetry, maximum, minimum and crest factor are selected in function of a greater contribution of infor-mation for the characterization of the experiment; these values generate databases that are applied for the crea-tion and training of a recurrent artificial neural network (RANN) in which an absolute error of less than 2% is obtained. In a first instance, the test methodology is applied to an engine assembled in a didactic work-bench, after which the method is applied to engines in vehicles.

Keywords: diagnosis, compression pressure, RANN, SIE, Elman Network, recurrent layer.

Resumen

En la presente investigación se realiza la explicación de la metodología aplicada a la determinación de la presión máxima de compresión de un motor de combustión interna alternativo de encendido provocado (MEP), el cual se basa en un estudio que parte de la caracterización de las curvas del consumo de amperaje del motor de arranque. Se aplica un protocolo de adquisición de datos y su posterior análisis estadístico. Los valores estadísticos de la señal como energía, promedio, desviación estándar, varianza, kurtosis, asimetría, máximo, mínimo y factor de cresta son seleccionados en función al mayor aporte de información para la caracterización del experimento; estos valores generan bases de datos las cuales son aplicadas para la creación y entrenamiento de una red neuronal artificial recurrente (RNAR) en la cual se obtiene un error absoluto menor al 2 %. En una primera instancia se aplica la metodología de pruebas en un motor ensamblado en un banco didáctico y luego se procede a la aplicación del método en motores aplicados en vehículos.

Palabras clave: diagnóstico, presión de compresión, RNAR, MEP, red Elman, capa recurrente.

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1. Introduction

Nowadays, the repair and diagnosis processes applied in the area of automotive transport range from artisanal schemes to those reaching a high technical level [1]. The daily increase in number of circulating vehicles demands specialized services, with a subsequent reduction in failure detection and repair times. This has led to the development of research through vibration analysis [2], in order to identify parameters of critical operation, experimental analysis of the acoustic emissions of reciprocating engines [3], non-intrusive determination of engine cylinder capacity [4].

Due to the complexity of the variables that intervene in the diagnosis of internal combustion engines, the application of computational mathematics is necessary.

The use of neural network techniques is considered to be a great contribution in the analysis of the parameters of internal combustion engines, according to Saraswati and Chand; cylinder pressure can be reconstructed with the use of a recurrent neural network (RNN) [5]. Likewise, in 2012 Cay and Cicek indicated that specific fuel consumption can be predicted based on parameters such as: engine braking, effective power, effective average pressure, and the temperature of the engine's exhaust gas. For this, an ANN model based on the standard backpropagation algorithm was used, with average errors of less than 3.8% [6].

According to Czarnigowski, it is possible to determine the spark advance value by using inverse neural network modeling of the effective torque, thus achieving idle speed stabilization [7].

The research of Wu, Huang and Chang proposes a fault diagnosis system of the ICE, based on the pressure of the intake manifold, by using Discrete Wavelet Transform (DWT) and RAN application. This type of diagnosis reduces the conventional defect of relying too much on the experience of technicians [8]. A very similar study was proposed by Shatnawi and Alkhassaweneh, where the sound signal emitted by the ICE is the source of information to discover faults, by means of an extension neuronal network (ENN), which improves performance compared to a RAN [9].

Efforts to predict future engine states are also of great interest in the technological development of engines, as demonstrated by a study developed by the University of Michigan, where RANs are used to predict combustion behavior of an ignition engine by homogeneous charge compression ignition (HCCI) during its transient operation [10].

With the same purpose of predicting the performance and exhaust emissions under different EGR strategies, researchers Roy, Banerjee and Bose present a study that uses RAN, obtaining, as a result, correlation coefficients within the range of 0.987–0.999 and an absolute error in the range of 1.1–4.57% [11]. For the purpose of optimizing RANs, parallel strategies can be used, such as the smooth variable structure filter (SVSF) used to train RANs efficiently, consequently known as SVSF-based RAN, which is used again for the detection and classification of engine faults using vibration data in the crankshaft angle domain [12].

Likewise, through the use of RANs, an automated diagnostic system for ignition failures in the ICE has been developed, which consists of three stages: detection, location and identification of failure severity [13].

Researchers Chen and Randall trained a RAN for time domain analysis that uses the parametric characteristics of acoustic emissions (AE), to detect damage to the valves of the ICE [14].

It should be noted that there are very few intelligent systems at the general level focused on the diagnosis of mechanical faults involving pressure compression of the EPI, with expert systems such as DELTA, by General Electric Company [15], used for the repair of diesel and electric locomotives. Another example is STEAMER [15], developed by the Navy Research Perssoner Development Center, designed to teach the operation of a steam propulsion plant such as those used in steam-powered vessels, and finally we can mention Project Eolo CN-235, developed by the Spanish company Construcciones Aeronáuticas S.A., an interactive teaching system for pilots and aircraft maintenance technicians, model CN-235.

At a commercial and academic level there are different softwares such as Autodata, which has technical specifications sheets and estimated repair times, fault codes, repair routines of different brands and models of cars, allowing technical personnel to perform any type of repair with the disadvantage of the subjectivity of the operators in decision-making based on trial and error in their professional experience, which maintains an incipient diagnostic system that in many cases could cause erroneous and deficient repairs to the automobile [1].

This bibliographic review leads to the investigation for the generation of methodologies put forth in order to determine the maximum compression pressure in the combustion chamber in spark-generated ignition engines, in a way that is minimally intrusive and quickly realizable.

2. Materials and methods

This section explores the main topics related to the selection of less invasive parameters, engine instrumentation, soft-ware design, data collection, validation of samples, and the creation and training of a RANN.

2.1. Selection of less invasive parameters

The main objective is to avoid the manipulation and disas-sembly of elements that would otherwise be necessary to access the spark plugs and install a leak tester or a compres-someter, for which the following options are considered: the measurement of the mass flow parameter of engine air, in-stalling a pressure gauge in the intake manifold [16], meas-uring the current consumption of the starter engine, measur-ing the battery's voltage drop. All these options involve the condition of the starter engine for a determined time period.

2.2. Engine instrumentation

The previous section outlines the measurement parameters for the development of the experiment, after which we see that a MAF type hot wire sensor can be used to perform the measurement of mass flow air intake, a MAP type sensor can be used for pressure measurement in the intake mani-fold, a clamp meter can be used for the measurement of the consumption current of the starter engine, a voltage divider connected directly to the battery terminals can be used for the determination of the voltage drop, all of which is shown in Table 1 and Figure 1.

Table 1. Engine instrumentation.

Parameters	Sensors
Mass flow of air	MAF
Intake pressure	MAP
Current	Clamp meter
Voltage	Divided voltage

To identify a cylinder that shows a significant difference in its compression value, an inductive clamp is applied to register the spark that corresponds to cylinder 1 and, ac-cording to ignition order, the cylinder with the greatest var-iation is located. The signal of the CMP sensor is registered to identify each of the cylinders in the engine on the test workbench.

Figure 1. Engine instrumentation.

For the application of the MAF sensor, several couplings are needed that depend on the diameter of the intake manifold, so this option is discarded as it also requires the disassembly of several conduits from the intake manifold. For the MAP application, a tap on the intake manifold must be identified which allows the sensor to be connected, which in some vehicles is non-existent. Therefore, conduits must be disconnected and can generate mechanical failures if they are not reinstalled correctly, and so this option is discarded.

Energy consumption of the starter engine can be measured with the installation of a clamp meter, for which no further requirements are needed, only the identification of the cable and the subsequent installation; voltage measurement is achieved direct-ly through the application of clamps on the battery terminals, indicated in Figure 2, without this option representing major complications.

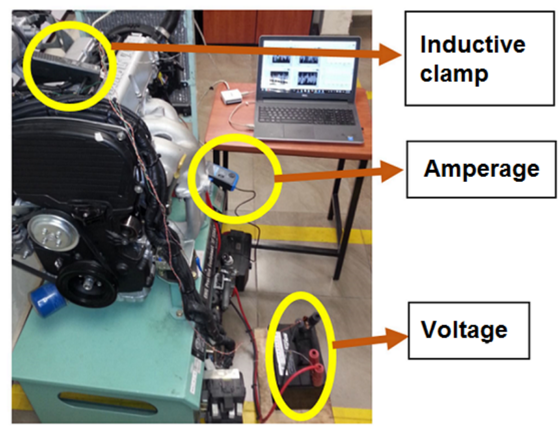
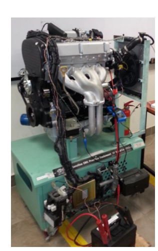


Figure 2. Measurement of battery amperage and voltage.

Table 2 summarizes the characteristics of the motor being tested and of the applied current clamp.

Table 2. Equipment

Graphic	Characteristics
SIE 	Hyundai 4 cylinders DOHC Electronic fuel injection (MFI) VT = 1997 cc ignited by spark / Unleaded petrol (RON 95) Rc = 10.0 : 1 MAP – DIS
Hantek CC – 650 	AC/DC Current Clamp Bandwidth 400 Hz 1 mV / 10 mA 650 A AC/DC frecuency range: Up to 400 Hz Effective Measurement range: 20 mA to 650 A DC

2.3. Software design

Once it is determined that amperage consumption, together with the measurement of the voltage drop, is the least invasive parameter, the LabView software, which is compatible with a Ni 6009 card, is used for the acquisition of data at a rate of 1 kHz, meeting the Nyquist criterion for signal analysis.

The software also performs the extraction of characteristic parameters and descriptive statistics of each test performed and, in addition, it generates a database which will subsequently be applied in the creation and training of a recurrent artificial neural network.

Figures: 3a, 3b and 3c present a sequence and part of the programming applied for the acquisition and development of the software and its graphic environment.

2.4. Data collection

The graphs resulting from the sampling of the studied engine, with differences in compression pressure (the engine is in starting condition), are shown below.

Figure 4 shows the compression pressure curve as a function of the oscillogram of the starter engine's am-perage consumption curve, in which the engine is in standard conditions, that is, all its cylinders present a standard compression pressure of about 125 PSI.

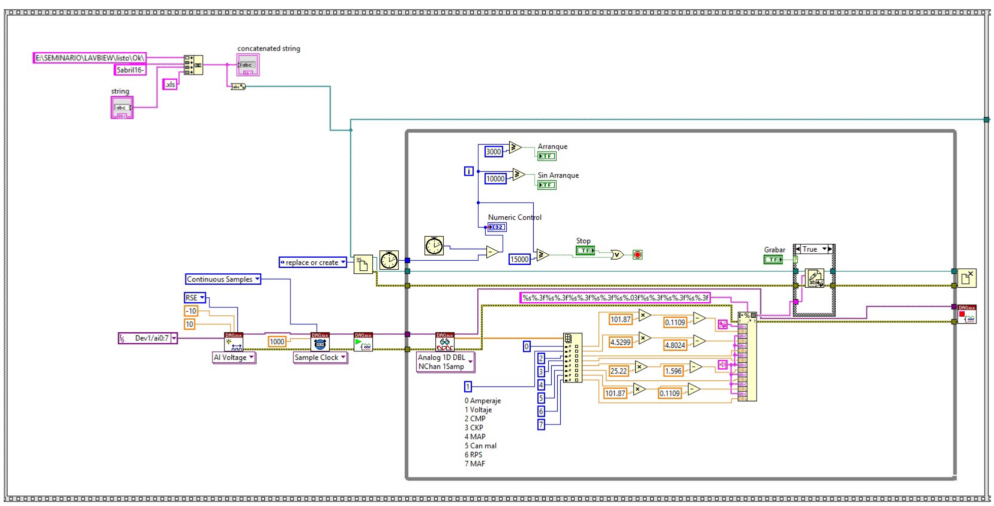


Figure 3a. Signal acquisition.

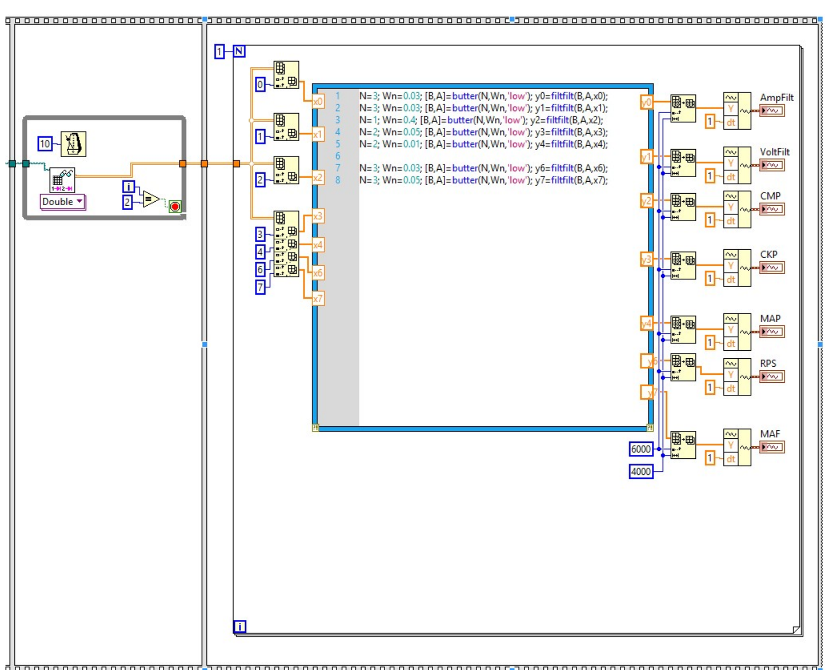


Figure 3b. Signal filtering, development and extraction.

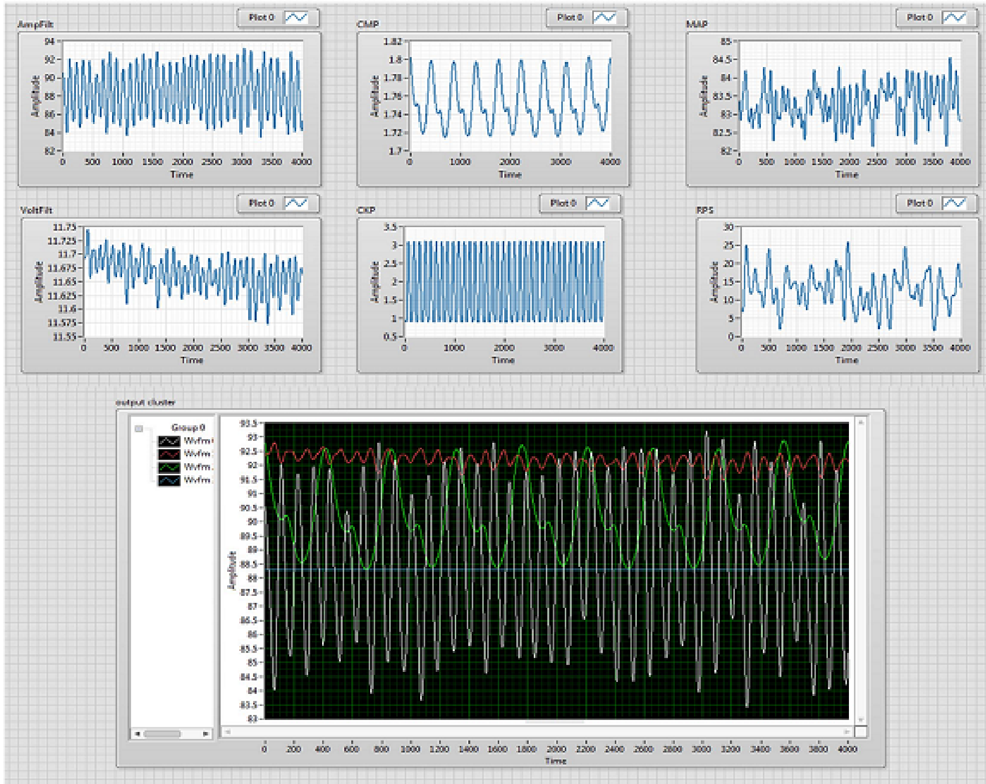


Figure 3c. Visualization of the signals and their graphic environment.

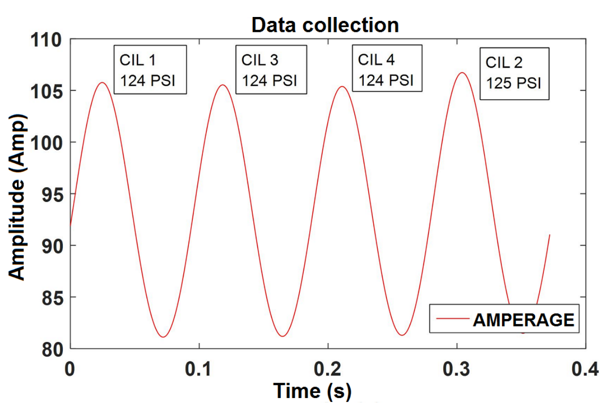


Figure 4. Engine data collection without major compression variation.

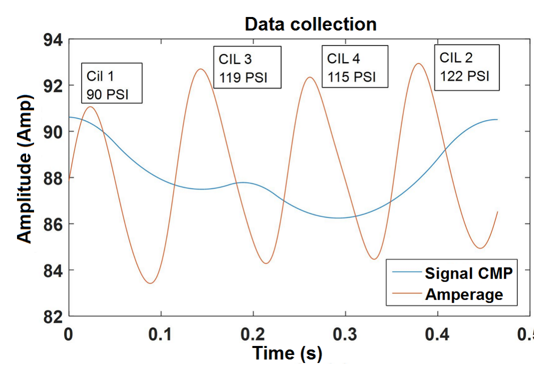


Figure 5. Engine data collection with compression variation in cylinder 1.

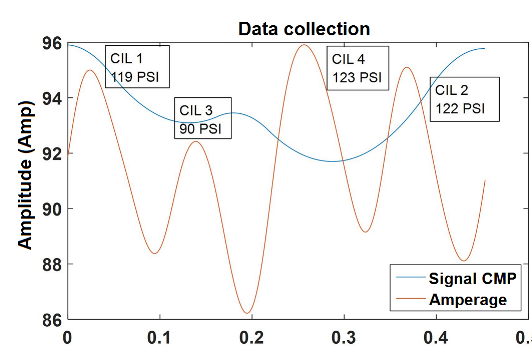


Figure 6. Engine data collection with compression variation in cylinder 3.

In Figures 5, 6, 7 and 8, the compression pressure curve is plotted according to the oscillogram of the starter engine's amperage consumption curve, in which the engine presents compression variations in each cylinder. This means that the cylinder corresponding to the ignition order has a compression pressure of 90 PSI, while the 3 remaining cylinders maintain their standard pressure. In addition, the signal curve of the CMP sensor can be identified.

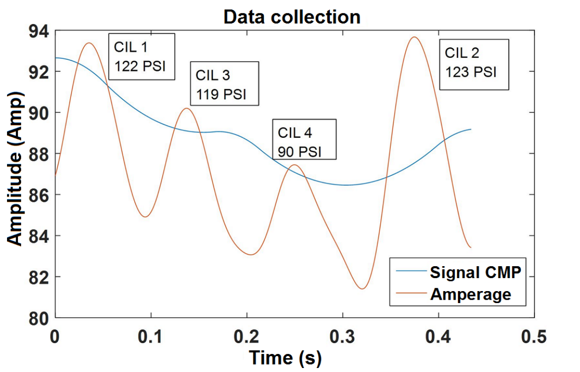


Figure 7. Engine data collection with compression variation in cylinder 4.

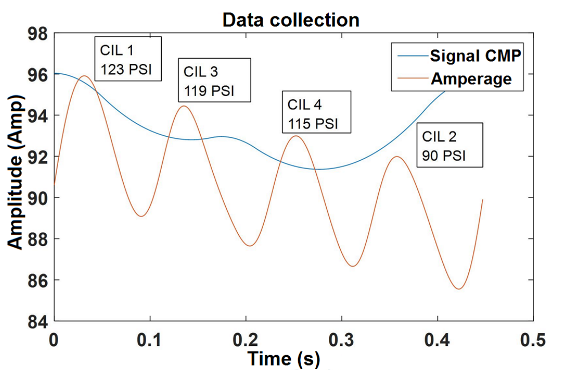


Figure 8. Engine data collection with compression variation in cylinder 2.

Next, in Figures 9, 10, 11 and 12 a bar diagram is applied, in which each bar represents the value of the compression pressure as a function of the amperage consumption of the starter engine when the engine presents compression pressure variations in each cylinder, that is, the cylinder corresponding to the 1-2-3-4 order has a compression pressure of 90 PSI, while the other 3 remaining cylinders maintain their standard pressure.

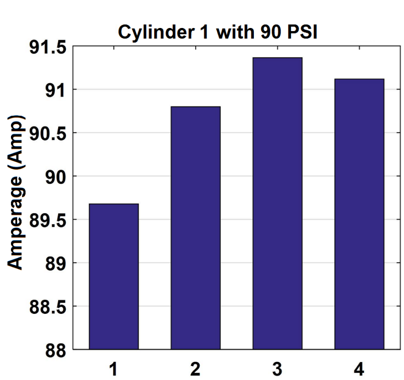


Figure 9. Engine with compression variation in cylinder 1.

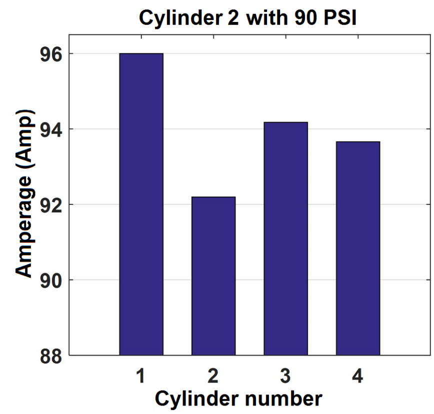


Figure 10. Figure 10. Engine with compression variation in cyl-inder 2.

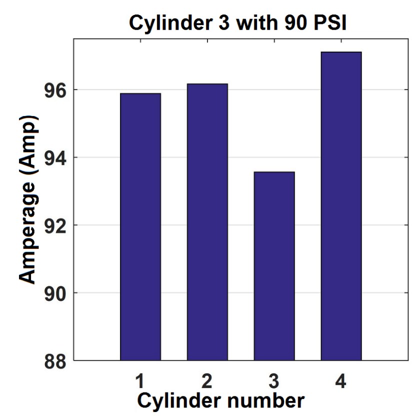


Figure 11. Engine with compression variation in cylinder 3.

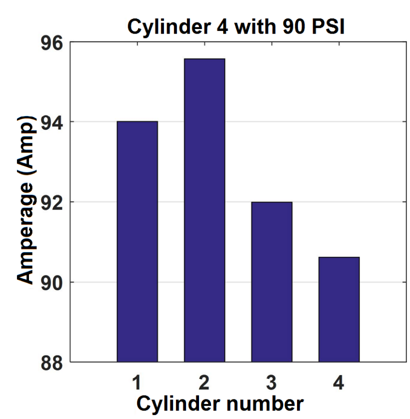


Figure 12. Engine with compression variation in cylinder 4.

2.5. Sample validation

The samples taken by the software designed in the LabView virtual platform are analyzed statistically through an ANOVA, which yields the following results.

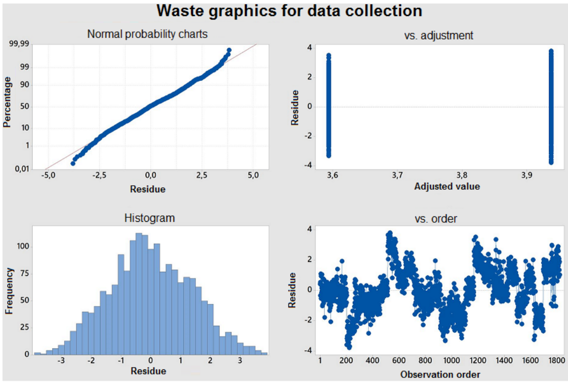


Figure 13. ANOVA of samples.

The scatter plot in the graph showing residual vs. percentage shown in Figure 13 tends to be a straight line which affirms the normality of the data and which, furthermore, is confirmed by the distribution of values in the form of the Gaussian bell in the histo-gram. The assumption of constant variance is validated because, in the graph for adjusted value vs residual value, no point accumulation pattern is observed. Ad-ditionally, this corroborates that the samples were ran-domized, since the point values in the observation order vs. residue graph show no regions of accumula-tion in the upper or lower part of zero. Rather, they fluctuate in a random pattern around the zero line.

In summary, the data collection is correct and the ANOVA results corroborate this fact.

To determine the most significant characteristic sta-tistical values, a unidirectional ANOVA is applied to the variables under study in order to analyze the p-value results, with the lowest value revealing the great-est significance of the variables. Next, Table 3 lists the statistical values in order of significance based on the lowest value of ρ.

Table 3. Equipment

Statistical values	***p-valúe***
Amp peak	0,000
Energy	0,000
Max	0,000
Mean	0,000
Standard Deviation	0,000
Variance	0,000
RMS	0,000
Asymmetry	0,000
F. Crest	0,001
Kurtosis	0,003

2.6. Elman type neuronal network

An Elman-type neural network is applied, based on a pre-experimental run in which trainings were carried out with different types of networks, including «feed-forward», «cascade-forward», «elman-forward». The one showing lesser errors was selected. Having made the previous observation, it is indicated that the input parameters are characteristic values resulting from the analysis of the amperage consumption curve of the starter engine; these are presented in Figure 14.

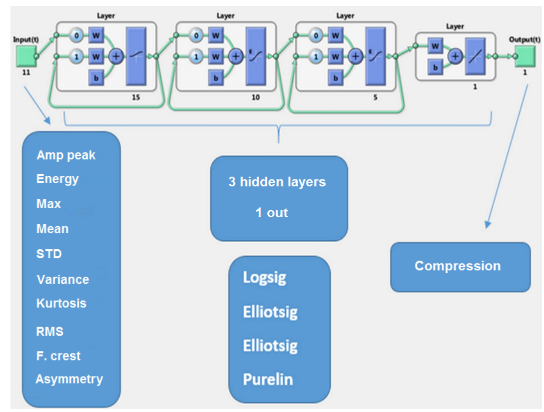


Figure 14. Elman-type neural network

Three hidden layers are applied, each with 15, 10 and 5 neurons per layer, due to the lower computa-tional expense, since increasing layers and neurons does not reduce error and the execution time increases. Moving forward, the activation functions between the input neuron and the first neuron are of the Logsig type, followed in the two layers by an Elliotsig func-tion, and finally between the layer and the output neu-ron a Purelin type function.

The output neuron indicates the value of the com-pression result, this according to the computational analysis generated by the Elman-type RANN.

The network training is done with the Levenberg-Marquardt function (trainlm), which is shown in Fig-ure 15.

Figure 16 indicates the gradient in the reduction of the squared error or MSE and the number of Epochs created for training the RANN.

3. Results and discussion

In order to compare the correct operation of the creat-ed and trained RANN according to the proposed pro-cess, several tests of various compression values are performed. In this section, two specific compressions are presented, with values ranging near 120 PSI in the case of engines operating correctly; another case is where the values are around 90 PSI, which indi-cates an imbal-ance fault in the engine's generalized combustion.

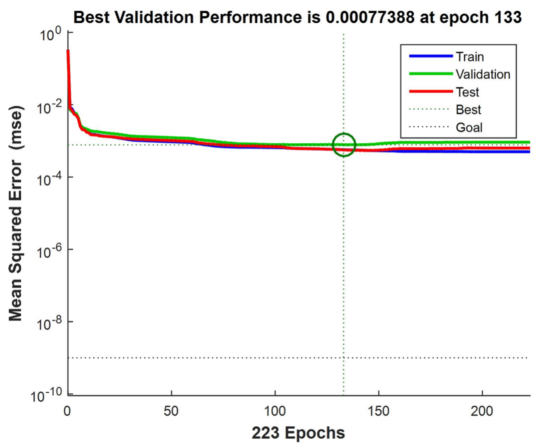


Figure 15. Elman-type network training.

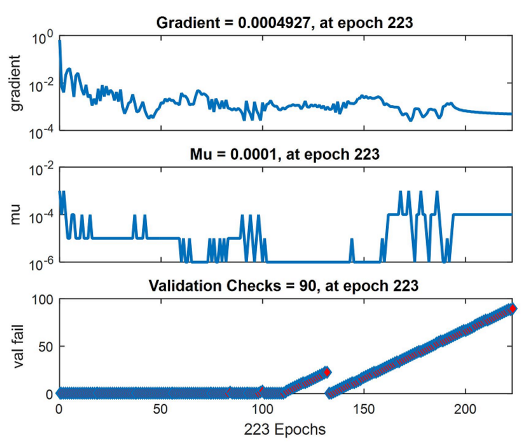


Figure 16. Evolution of Elman-type network training.

Figure 17 shows the result of the values obtained by the RANN for 120 PSI compression sockets, where the average value of the resulting error and the real value is 0.0895% of the absolute value.

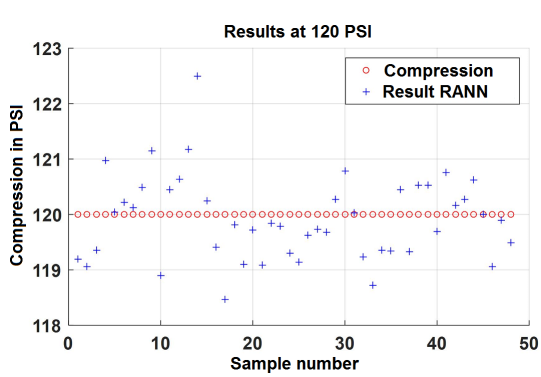


Figure 17. Compression results at 120 PSI.

Figure 18 shows the result of the values obtained by the RANN for 90 PSI compression sockets, where the average value of the resulting error and the real value is 0.2591% of the absolute value.

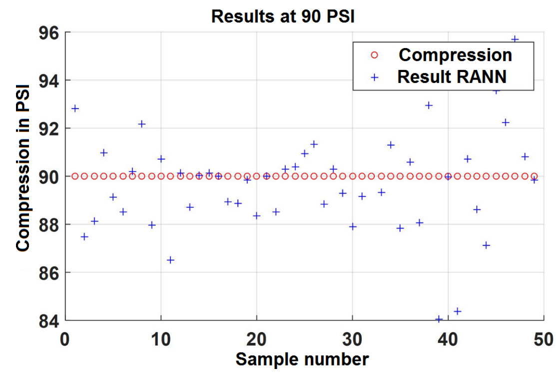


Figure 18. Compression results at 90 PSI.

4. Conclusions

This work demonstrates that the application of recurrent artificial neural networks (RANN) in the determination of the compression of an SIE constitutes a clearly viable alternative; in addition, it has the advantage of being minimally invasive with error ranges of less than 1%, and with the possibility of determin-ing the compression value with a high degree of probability.

Another fundamental aspect to take into account is that the compression measurement process is applied very frequently in the evaluation of vehicles for sales. Therefore, this methodology is presented as a highly appropriate technique to be integrated into a diagnostic system with the computational speed that neural net-works offer.

After the elaboration of this study, in which an Elman-type neuronal network structure is applied, it has been observed that this is the most appropriate given the dynamic nature of the patterns obtained by the analysis of the starter engine's energy consumption.

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