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Embedded integer NARX identification of knocking combustion of large gas engine

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***Abstract*— Embedded integer NARX (nonlinear autoregressive neural network with exogenous inputs) identification of the vibration experiments on knocking combustion of a Deutz MWM 8 cylinder large gas engine was carried. A measure of the degree of dependence of vibration and knocking reference values defined by the NARX recurrent neural network. A new identification is proposed based on the cross-correlation between the vibration signal and neural network error.**

I. INTRODUCTION

Knocking phenomena in combustion processes were observed from the very beginning of the large gas engine research [1]. Knocking may cause fluctuations in the mechanical part of the engine as well as fluctuations of the burned gas. As a consequence, the mean torque may be cuted down by as much as 40% [2][3]. It is therefore not revealing, that detecting and predicting knocking phenomena were identified as a basic engineering problem in large gas engines [4].

Knocking is an abnormal condition where partial combustion built of the gas or gasoline/air mixture during the power stroke of the internal combustion engine. *Engine knock is a very specific nonlinear, chaotic problem* where gas "detonates" from pressure and not spark ignition [5][6].

The knock usually happens when the air/gas or gasoline mixture is too lean (too much O_2) or the ignition timing is too far advanced. There is a distinctive knocking noise associated with this dilemma [7][8]. The serious problem during gas engine operation, the changes of natural gas quality [9]]10].

A complicated issue of knocking combustion is the unpredictable nature of their appearance, resulting the gas engine control as a challenging task [11][12]. Understanding of their origins have been one of the main subject in large gas engine technology in the last century [13][14]. However, based on the exercise made in interpreting the different basics of knocking instabilities in the previous time, the problem of a robust system management in a large gas engine has not been clarified yet [15][16][17].

The elemental units of knocking fluctuations are:

i. Nonlinear, chaotic instabilities in the combustion chamber throughout combustion, [18][19]
ii. quality- [20],
iii. amounts of gas,
iv. distribution of the local blend near the combustion occlusion [21][22].

Recent publications concentrated on the development and utilize of spectral models of the knocking procedure. Among the different articles, Millo and Ferraro [23], Abu- Quadis [24] and Taglialatela et al. [25] analyzed the nonlinear character of knocking and studied the system of vibration fluctuations in a gas engine.

Using a spectral analysis, in [26][27][28] published the working cycle of the knocking parameters along with combustion pressure. Later, Thomas et al. [29] analyzed the gas circulation in a nonlinear model considering engine dynamics.

The most plausible feature for the presence of nonlinear dynamics in the large gas knocking phenomena derived from the theory of time irreversibility of the combustion thermodynamics of Wu [30] and Thomas [31].

In this paper we present knocking vibration signal analysis of a Deutz MWM gas engine. [32][33]. We describe a method that gives a nonlinear exogenous representation of vibration system, i.e., that provides dynamical information on the knocking environment. The knocking system is taken as quasiperiodic and chaotic, meanwhile the time-frequency representation is revealing, because it shows when and how knocking motion between adjacent signals can be trapped in some resonance zones associated with quasi periodicity [34][35][36]. In our studies we apply nonlinear autoregressive identification (NARX [37][38][39][40]) between the vibration signal and knocking reference.

Nonlinear system identification has been used to analyze the knocking system in [38] where the main frequency was extracted by computing the frequency curve where the energy is maximum.

In our work in Sec. II, we describe the NARX system and in Sec. III, introduce the NARX neural network approximation for knocking parameter. In Sec. IV. we present the results.

II. NONLINEAR AUTOREGRESSIVE NEURAL NETS WITH EXOGENOUS PARAMETER

For the large gas engine vibration signal knocking project we use nonlinear autoregressive model with exogenous inputs (NARX [34][35][36][37][38][39][40]). The model being approximated by a variant of recurrent neural network that has been successful utilized in the engine diagnostics [42]. In the following we call the recurrent network as *NARX neural network*. The major difference between recurrent and feedforward network is, recurrent net allows a weighted feedback connection between layers of neurons and thereby making it suitable for engineering knocking prediction by allowing lagged values of variables to be considered in model. Although the literature many time series methods such autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), etc. have been applied in various industrial problems, these techniques cannot manage nonlinear problems [39][40].

The conditions of the recurrent neural network approximation of NARX system in the knocking combustion project could be summarized as:

- *learning* is more sufficient in recurrent networks than in alternative neural network (gradient descent method [43]).

- the recurrent networks *converge* much spirited than other networks [44].

- *integer* representation for embedded microcontroller environment of the NARX neural network is uncomplicated achievable. [45].

Throughout, we focus our attention to the knocking vibration analysis by an *input-output representation* of discrete vibration and knocking reference signals, which could be encapsulated:

$$y(t)=f[U(t-DU),\ldots\ldots,U(t-1),U(t),Y(t-Dy),\ldots\ldots,Y(t-1)] \quad (1)$$

where *U(t)* and *Y(t)* demonstrate input (vibration signals) and output (knocking references) of the network at time *t*. *Du* and *Dy*, are the input and output order (or delay), and f is a universal nonlinear function which could be represented by NARX neural network gauging function Ψ. (see Eq.2).

For instance we could select for NARX neural networks zero input order and a D-dimensional output. i.e., retaining D elements feedback from output alone: the main operation equation of NARX neural network is driven now by:

$$Y(t)=\Psi[U(t),Y(t-1),\ldots\ldots Y(t-D)] \quad (2)$$

where Ψ is the NARX gauging function. The simplified structure of NARX neural network is represented in figure 1.

However, publications diverse engine control systems present, that recurrent neural networks are regularly much improved at disclosing long time–dependences than conventional neural networks [46][47],.

In recent times, in engine controlling certain recurrent neural network applications have demonstrated [48], it could be ambitious to design the net learning with stability. Deng et al. [47] considered diverse learning algorithms for structures with long time inherent dependencies and presented, that for gradient-based training algorithms the gradient vanishes for large *m* iteration steps. This event is assigned to as the issue of *vanishing gradients*, which demonstrate why gradient descent methods could be an issue *to interpret structures with chaotic long-term dependencies, presenting in the engineering knock signals* [48].

To avoid the problem of *vanishing gradient* in learning and training the NARX network in the literature some article is engaged with introducing *integer embedding memory* in recurrent neural networks [40], whereas certain others recommend enhanced *robust learning algorithms*, such as the stochastic Kalman filter, Gauss-Newton algorithm and simulated annealing [41][42][43].

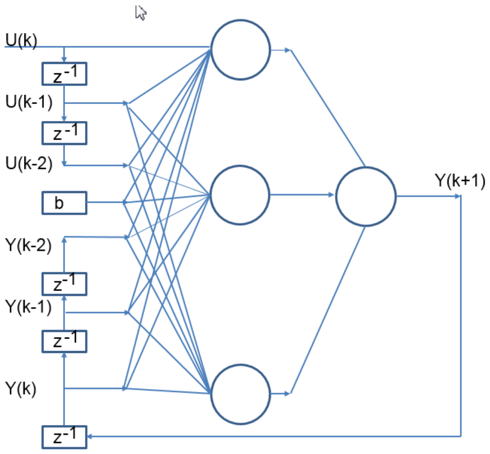

Fig. 1. NARX architecture: U(k) are the input vibration values, Y(k) are the reference outputs, b – tapped bias; where the next value of the vibration signal Y(t) is regressed on previous values of the vibration signal and previous values of an independent (now exogenous) knocking reference signal.

III. RESULTS

A. Applied integer NARX structure, functions

We implement the NARX model with a recurrent neural network based on a modified Matlab Ver. 2016b Neural Network Toolbox [49], to approximate the NARX gauging function Ψ between the vibration values and the knocking reference.

The recurrent neural network Matlab source has been modified with

- the integer embedded memory (Figure 1), as a delayed neuron from the reference output of the second layer to the vibration input being introduced,
- the integer sigmoid activation function [47].

During the definition phase it was observed, that the learning process could be accelerated by *simultaneously analyzing* the input, vibration series. For example, the reference value could be better “predicted”, if 12 input vibration values partitioned to 6+6 values and together with the last 1 reference value *simultaneously applied as inputs* to the neural networks. The new NARX neural network learning model can be seen on the Fig.2. The representation deriving from the Figure 1 and for example NN(*du*, *dy*; *12*) denotes the NARX with *du* input delays, *dy* output delays and 6+6 (vibration) neurons in input layer.

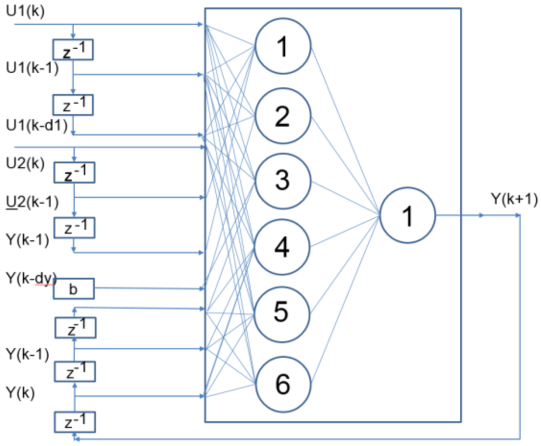

Fig. 2. Modified NARX architecture with two tapped delay biases and 6 hidden neurons for partitioned (U1, U2) input signals and reference signal (Y)

The common formalism for the generalized integer architecture (Figure 1) for the reference signal *Y*(*k*+1) based on the previous vibration values *U*(*k*), *U*(*k*-1), …, *U*(*k*-*dU*) and the actual and previous reference values *Y*(*k*), *Y*(*k*-1), …, *Y*(*k*-*dY*) as inputs, could be drafted as

$$Y(k+1)=\Psi_0\left[w_{b0}+\sum_{k=1}^{N}w_{h0}\Psi_h\left(w_{h0}+\sum_{i=0}^{du}w_{ih}U(k-i)\right)\right]$$
$$+\sum_{j=0}^{dy}w_{jh}Y(k-j) \qquad (3)$$

For the modified integer NARX neural network model in Figure 2, the reference *Y*(*k*+1) based on the previous observations *U*1(*k*), *U*1(*k*-1), …, *U*1(*k*-*dU*) for the first vibration series, the previous observations *U*2(*k*), *U*2(*k*-1), …, *U*2(*k*-*dU*) for the second vibration series and the previous references *Y*(*k*), *Y*(*k*-1), …, *Y*(*k*-*dY*) as inputs, could be formulated as:

$$Y(k+1)=\Psi_0\left[w_{b0}+\sum_{k=1}^{N}w_{h0}\Psi_h\left(w_{h0}+\sum_{i1=0}^{du1}w_{1ih}U1(k-i1)\right)\right]$$
$$+\sum_{i2=0}^{du2}w_{i2h}U2(k-i2)+\sum_{j=0}^{dy}w_{jh}Y(k-j) \qquad (4)$$

B. *NARX learning*

Determining the recurrent learning gradients a *dynamic* algorithm is required [47]. The mathematical structure of the back-propagation error for dynamic NARX systems is more complicated than those for static networks [48]. The NARX neural network training system applies the improvement of using the actual, measured (aka *unlearned*) reference value, which is more conceivable instead of the evaluated output to train the NARX neural network. This dynamical network has an *averaged* feedforward structure and can be trained with usual static back-propagation algorithm. Furthermore, the knocking references to the feedforward network are just the *real/true ones* (together with the evaluated ones), and the training is more exact.

However, the process has some limitations. One is associated to the sum of parameters and to the number of hidden neurons to be involved in NARX neural network. Commonly, this number could be considerable and there is a risk of "overfitting" the data generating an incorrect solution, which does not lead to adequate knocking vibration values.

The solution of the overfitting could be to clustering the neurons [16][29][33]. This fact inspires the use of an algorithm including the regularization method [16][19], which concerns adjusting the performance function for reducing the neurons weight.

The common *learning integer performance function* realization used in training:

$$\frac{1}{N}\sum_{i=0}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=0}^{N}(t_i + \mathrm{int}(Y_i))^2 \qquad (5)$$

could be replaced by

$$k * \frac{1}{N}\sum_{i=0}^{N}(t_i + \mathrm{int}(Y_i))^2 + (100 - k) * \frac{1}{N}\sum_{i=0}^{N}(w_i)^2$$
(6)

where t_i is the reference knocking value and $k<100$ is the integer performance factor [36]. The performance function is account for the smaller neuron weights and biases, and accelerates the network answer being stable and steady.

C. *NARX training*

We use for the NARX training the modified Levenberg-Marquardt optimization to include the regularization technique [16][19]. It minimizes a sequence of errors and weights and determines the appropriate combination. The process could be labeled as Bayesian regularization [43]. Typically, in function optimization problems, for networks that consist of few hundred weights, the Levenberg-Marquardt algorithm have agile convergence [41]. This benefit is principally apparent if high-accurate training is prescribed. However, as the number of weights in the network increments, the convergence of this algorithm changes.

We use for the NARX training *preprocessing stage* on the network inputs and targets as following:

- normalization of the vibration and knocking through to [-100, 100]. This simplifies the chaotic issue of the knocking signals.
- in all engine experiments, an one-step-ahead knocking combustion prediction is investigated; that is, the actual measured references of all lagged experiments are used as recurrent inputs.
- if more than one reference predictions are required then, it is possible to progress by computing the first one-step ahead reference to vibration series, and then the second vibration series is treated to maintaining the second step-ahead.

D. *Detecting knocking combustion with the modified NARX Matlab Neural Network Toolbox code-basis*

Detecting and learning knocking combustion, various NARX neural network parameters have been modified:

- number of lagged vibration input steps
- of lagged output recurrent steps as inputs,
- and different number of neurons in layer 1 and layer 2

All the network topologies include

- 12+1+1 inputs (6+6 vibration and 1 reference value and 1 recurrent reference value)
- layer 1 with 10 neurons, and
- single neuron in layer 2 (output layer).

The input has been rescaled in most cases to be included in [-100, 100] range (Figure 3).

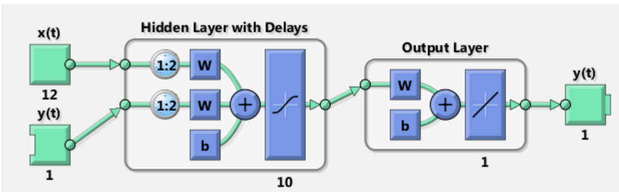

Fig. 3. For vibration knocking analysis, Matlab NN Toolbox [45] NARX module with recurrent neural network used.

It is known, that by NARX learning the input variables could be uncorrelated, because the interacting input variables may downgrading the detection rate by relating with each other likewise other components and generating a biased issue [48].

Analyzing the vibration signals the Deutz MWM 8 cylinder large gas engine system we found, that a recurrent NARX neural network model with 13 inputs and 10 hidden neurons points to high detection-rate and for the integer embedded microcontroller environment is applicable.

We recognized for the learning the knocking references, that the optimum number of lags could fit in 15-30 range, the appropriate value being treasured from one case to another. A higher number of lags at input do not revise the learning efficiency and the knocking combustion detection. A contrary case in choosing the number of lags of the delay: a higher number should satisfy, that the input sequence for detection possible, but another parameters are correlated to eliminate distorted detections.

For illustration on the Figure 4 the weak knocking vibration signals of the MWM Deutz engine between the working cycles 288-336 can be seen. The first and third beat junctions are originated from valve effects, the second junction is the combustion.

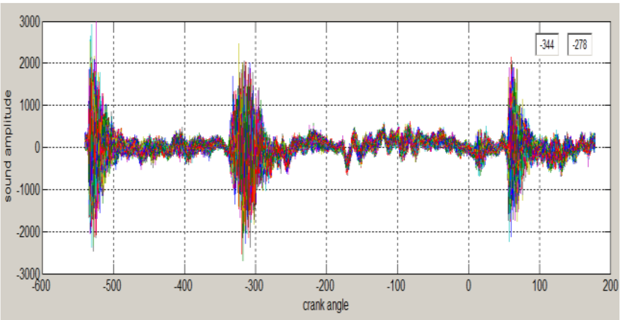

Fig. 4. Weak knocking vibration signals of MWM G234V8 Deutz large gas engine. Working cycles 288-336. Combustion at crank angle -312°. The events at -540° and/or at 75° are the engine valve impulses.

The whole system for this experiment (7569 working cycles) of the neural results on the Fig. 5. can be demonstrated.

We analyzed 50 knocking experiments. For the 12+1 inputs and 10 hidden neurons the target errors (Figure 4) for the whole modified NARX system are less than 9%.

The knocking phenomena based on the trained NARX neural network can be measured by cross-correlating the network errors on the training with the vibration signal (Figure 5). The cross-correlation value is a measure of the variation between the generated outputs and targets. If this number is equal to 1, then there is perfect correlation between the targets and outputs and could be characterized as *weak knocking system*.

If the training error is equal to 0, then the signal is chaotic and the long term memory dependence is disturbed, the signal shows strong knocking singularities.

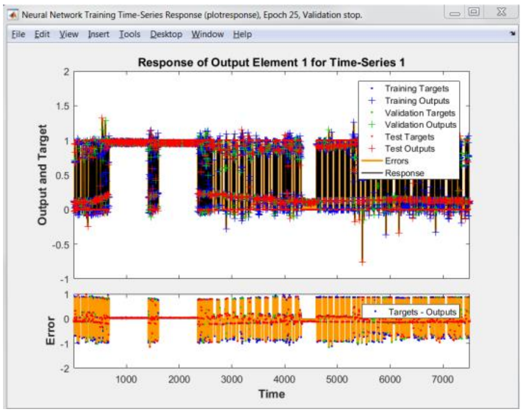

Fig. 4. Upper picture: knocking working cycles, down identification failure.

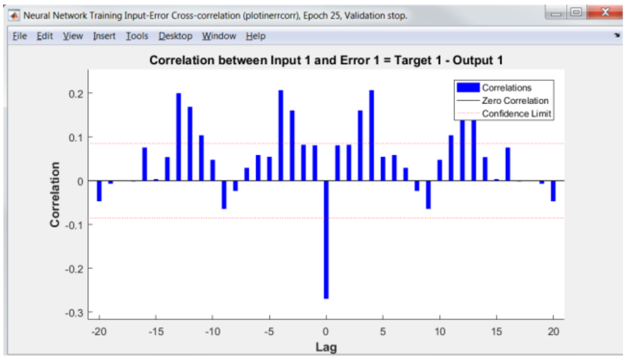

Fig. 5. Cross correlation between the vibration and the hidden neuron

We compare the identification results of two methods widely used in the large engine knocking environment: the wavelet [26] and the band-pass filtering [27] methods for 50 different engine experiments with more than 10^9 working cycles. Our first result is presented in Fig.6. The obtained correlation coefficients are harmonic, compatible with the wavelet and band-pass filtering method and show us, that the difference between the three methods are small enough to be accepted.

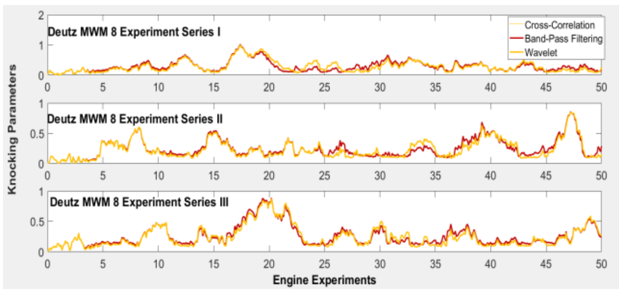

Fig. 6. Comparing three methods for the knocking combustion characteristic of 50 combustion experiments of the Deutz MWM 8 cylider large gas engine: wavelet [26], band-pass filtering [27] and the cross-correlation presented here.

IV. CONCLUSIONS

In this paper we showed vibration knocking analysis based on nonlinear autoregressive exogenous model (NARX). The model have been apprioximated by recurrent neural networks. We demonstrated the NARX neural identification of the knocking characteristic based on the experiments of a Deutz MWM 8 cylinder large gas engine. The main idea was to cross-correlating the NARX neural network error function with the vibration input signal, and the cross-correlation value acts a measure of the knocking combustion.. The proposed integer NARX architecture was with 12 vibration-, 1 recurrent knocking reference-, and 1 actual knocking reference value as input, and 10 neurons as hidden layer. The identification fact indicates that the embedded real time realization of a neural network in the large gas engine controlling could give accurate information about knocking combustion.

REFERENCES

[1] Heywood, J., "Internal combustion engine fundamentals", Springer Verlag. 1988.
[2] Millo, C., "Knock in S.I. Engines", SAE Paper 9824 1988.
[3] Serikov S. A., "Neural network model of internal combustion engine", Cybernetics and System Analysis Nov.2010. Vol. 46. Pp. 998-1007.
[4] Witwit, A.R. et al., "Modern methods in engine knock signal detection", Procedia Technology. Vol. 11. 2013. Pp. 40-50.
[5] Siano, D. – Bozza, F. "Knock detection in a turbocharged S.I.. engine based on ARMA technique and chemical kinetics", SAE International 2013. doi:10.4271/2013-01-2510
[6] Chun, K. and Heywood, J., "Characterization of Knock in a Spark-Ignition Engine", SAE Technical Paper 890156, 1989, doi:10.4271/890156.
[7] Ettefagh M.M., Sadeghi M.H., Prrouzpanah V., Arjmandi H. Tash, "Knock detection in spark ignition engines by vibrational analysis of cylinder block: A parametric modeling approach", Mechanical Systems and Signal Processing Journal, 22, pp. 1495-1514, 2008.
[8] Hu, H. and Keck, J., "Autoignition of Adiabatically Compressed Combustible Gas Mixtures", SAE Technical Paper 872110, 1987, doi:10.4271/872110.
[9] Keck J., Hu H., "Explosions of Adiabatically Compressed Gases in a Constant Volume Bomb, 21st International Symposium on Combustion", The Combustion Institute, pp. 521-529, 1986.
[10] Tanaka S., Ayala F., Keck J., "A Reduced Chemical Kinetic Model for HCCI Combustion of Primary Reference Fuels", Cmb. & Flame, 132, pp. 219-239, 2003.
[11] Garg, A. B., Diwan, P., Saxena, M. (2012), "Artificial Neural Networks based Methodologies for Optimization of Engine Operations, International", Journal of Scientific & Engineering Research, Volume 3, Issue 5, ISSN 2229-5518
[12] Kavaris, C. - Kantor J., "Geometric methods for nonlinear process control", Ind. Eng. Chem. Res. 1990 29 Pp. 2995-3012.
[13] Duval L et al., "Noise robust spark ignition engine knock detection with redundant wavelet transform", www.laurent-duval.eu.
[14] Ker S. et al. "Algorithm comparison for real time knock detection", www.laurent-duval.eu.
[15] Wu et al., "Control Design for Residual Gas Fraction in Engine Based on Stochastic Logical Dynamics", SICE Annual Conference 2015.
[16] Corcione, F., Siano, D., Vaglieco, B., Corcione, G. et al., "Analysis and Control of Noise Emissions of a Small Single Cylinder D.I. Diesel Engine", SAE Technical Paper 2003-01-1459, 2003, doi:10.4271/2003-01-1459.
[17] Esposito Corcione F., Siano D., Iadevaia M., Viscardi M., Esposito Corcione G., "Correlation between the acoustic intensity measurements with and without an electronically fuel injection system for a small single cylinder", Acta Acustica united with Acustica, Volume 89, Issue SUPP., May 2003, Pages S33.
[18] Kearney, M., Knock Signal Conditioning Using the Discrete Fourier Transform and Variable Detection Window Length", SAE Technical Paper 2007-01-1509, 2007, doi:10.4271/2007-01-1509.
[19] Antoni J., Daniere J., Guillet F., "Effective vibration analysis of IC engines using cyclostationarity. Part I. A methodology for condition monitoring", Journal of Sound and Vibration 257 (5) (2002) 815-837.
[20] Bozza, F., Siano, D., and Torella, E., "Cycle-by-Cycle Analysis, Knock Modeling and Spark-Advance Setting of a "Downsized" Spark-Ignition Turbocharged Engine", *SAE Int. J. Engines* 2(2):381-389, 2009, doi:10.4271/2009-24-0020.
[21] Zhen X., Wang Y., Xu S., Zhu Y., Tao C., Xu T., Song M., "The Engine Knock Analysis - An Overview", Applied Energy, 92 (2012) 628-636
[22] Brecq G., Bellettre J., Tazerout M., "A new indicator for knock detection in gas SI engines", International Journal of Thermal Sciences 42 (2003) 523-532
[23] Millo, F. and Ferraro, C., "Knock in S.I. Engines: A Comparison between Different Techniques for Detection and Control", SAE Technical Paper 982477, 1998, doi:10.4271/982477.
[24] Abu-Qudais M., "Exhaust Gas Temperature for Knock Detection and Control in Spark Ignition Engine, Energy Convers". Mgmt, Vol. 37, No. 9, pp. 1383-1392, 1996
[25] Taglialatela, F., Moselli, G., and Lavorgna, M., "Engine Knock Detection and Control Using In-cylinder Pressure Signal and Soft Computing Techniques", SAE Technical Paper, 7th International Conference, doi:10.4271/2005-24-061, 2005.
[26] Leppard, W., and Engineers, S. o. A., "Individual-cylinder knock occurrence and intensity in multicylinder engines", Society of Automotive Engineers, 400; Commonwealth Dr, Warrendale, PA, 15096, USA, 1982.
[27] Puzinauskas, P. V., and Engineers, S. o. A., "Examination of methods used to characterize engine knock", Society of Automotive Engineers, 400 Commonwealth Dr, Warrendale, PA, 15096, USA, 1992.
[28] Chatlatanagulchai, W., Yaovaja, K., Rhienprayoon-PTT, S., and Wannatong - K., "Fuzzy Knock Control of Diesel Dual -Fuel Engine". SAE Technical Paper, 01-0690, 2011.

[29] Thomas J.R., Clarke D.P., Collins J.M., Sakonji T., Ikeda K., Shoji F., Furushima K., "A test to evaluate the influences of natural gas composition and knock intensity", Trans. ASME J. ICE 22, 1994.

[30] Wu, et al.., "A Real Time Statistical Method for Engine Knock Detection", SAE Technical Paper 2007-01-1507, 2007, doi:10.4271/2007-01-1507.

[31] Thomas J.H., Dubuisson B., Dillies-Peltier M.A., "Engine knock detection from vibration signals using pattern recognition", Meccanica 32 (1997) 431-439.

[32] GE Jenbacher | "Gas engines", Clarke-energy.com. 2013-09-28.

[33] start your engines! - gas-engines. Library. thinkquest. org. 2013.

[34] I.J. Leontaritis and S.A. Billings. "Input-output parametric models for non-linear systems. Part I: deterministic non-linear systems". Int. J of Control 41:303-328, 1985.

[35] I.J. Leontaritis and S.A. Billings. "Input-output parametric models for non-linear systems. Part II: stochastic non-linear systems". Int. J of Control 41:329-344, 1985.

[36] O. Nelles. "Nonlinear System Identification". Springer Berlin, 2000.

[37] Chen S., Billings S.A., "Representation of nonlinear systems: the NARMA model", International Journal of Control 49 (3) (1989) 1013-1032.

[38] Billings, S. 1A.. "Nonlinear System Identification: NARMAX Methods in the Time, Frequency, and Spatio-Temporal Domains, Wiley, 2013.

[39] Billings S.A., Tsang K.M., "Spectral analysis for nonlinear systems. Part I: Parametric non-linear spectral analysis", Mechanical Systems and Signal Processing 3 (1989) 319-339.

[40] Siano D., "An ARMA Technique for Knock Detection by Using Vibrational Data Acquired on a Four Cylinder Turbocharged S.I. Engine", Journal of Mechanical Systems and Signal Processing, 2013

[41] Kreyszig E., "Advanced Engineering Mathematics", 9th ed., Wiley, 2006, Ch. 24, Sect. 24.

[42] Yue S. and Li P., "Automatic knock control system", In Intelligent Control and Automation, 2004. WCICA 2004. Fifth World Congress on, IEEE, Vol. 3, 2004, p.2464-2466.

[43] Wu B., Zoran F., Denise M. K, Gregory L. Ohl, Michael J. Prucka and Eugene Di Valentin (2004) "Using Artificial Neural Networks for Representing the Air Flow Rate through a 2.4 Liter VVT Engine", SAE international 2004-01-3054, Powertrain & Fluid Systems Conference and Exhibition Tampa, Florida USA October 25-28, 2004

[44] Gisca V, Mereacre A. and Pisarenco M., (2004) "Utilization of Neural Networks for Observing the Internal Combustion Engine's Function", 7th International Conference on Development and Application Systems, Suceava, Romania, May 27-29.

[45] Puig-Arnavat, M., Hernandez, J. A., Bruno, J. C., Coronas, A. (2013), "Artificial Neural Network Models for Biomass Gasification in Fluidized Bed Gasifiers", Elsevier, Biomass and Bioenergy 49 279e289

[46] Yusuf, C. (2013), "Prediction of a Gasoline Engine Performance with Artificial Neural Network", Elsevier, Fuel 111 324–331

[47] Deng, et al. (2011), "The Applications of Artificial Neural Networks to Engines, Artificial Neural Networks - Industrial and Control Engineering Applications", ISBN 978-953-307-220-3

[48] Garson, G.D. (1991), "Interpreting neural-network connection weights", AI Expert; 6:47e51.

[49] Mathworks Inc. Matlab 2016b. Computer Algebra Software 2016.